# Analysis of Decision Support Systems of Industrial Relevance: Application Potential of Fuzzy and Grey Set Theories

*Dissertation submitted in partial fulfillment*

*of the requirement of the degree of*

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*By*

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(Roll Number. 513ME1058)

*based on the research carried out*
*under the supervision of*

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*and*

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This is to certify that the work presented in the dissertation entitled ***Analysis of Decision Support Systems of Industrial Relevance: Application Potential of Fuzzy and Grey Set Theories*** by ***Dilip Kumar Sen***, Roll Number **513ME1058**, is a record of original research carried out by him under our supervision and guidance in partial fulfillment of the requirements of the degree of ***Doctor of Philosophy*** in ***Mechanical Engineering***. Neither this dissertation nor any part of it has been submitted earlier for any degree or diploma to any institute or university in India or abroad.

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# *Dedication*

*This dissertation is dedicated to my parents*
*for their love, endless support*
*and encouragement.*

# Declaration of Originality

I, ***Dilip Kumar Sen***, Roll Number ***513ME1058***, hereby declare that this dissertation entitled ***Analysis of Decision Support Systems of Industrial Relevance: Application Potential of Fuzzy and Grey Set Theories*** presents my original work carried out as a doctoral student of NIT Rourkela and, to the best of my knowledge, contains no material previously published or written by another person, nor any material presented by me for the award of any degree or diploma of NIT Rourkela or any other institution. Any contribution made to this research by others, with whom I have worked at NIT Rourkela or elsewhere, is explicitly acknowledged in the dissertation. Works of other authors cited in this dissertation have been duly acknowledged under the sections 'Reference'. I have also submitted my original research records to the scrutiny committee for evaluation of my dissertation.

I am fully aware that in case of any non-compliance detected in future, the Senate of NIT Rourkela may withdraw the degree awarded to me on the basis of the present dissertation.

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NIT Rourkela | Dilip Kumar Sen

# Abstract

The present work articulates few case empirical studies on decision making in industrial context. Development of variety of Decision Support System (DSS) under uncertainty and vague information is attempted herein. The study emphases on five important decision making domains where effective decision making may surely enhance overall performance of the organization. The focused territories of this work are i) robot selection, ii) g-resilient supplier selection, iii) third party logistics (3PL) service provider selection, iv) assessment of supply chain's g-resilient index and v) risk assessment in e-commerce exercises.

Firstly, decision support systems in relation to robot selection are conceptualized through adaptation to fuzzy set theory in integration with TODIM and PROMETHEE approach, Grey set theory is also found useful in this regard; and is combined with TODIM approach to identify the best robot alternative. In this work, an attempt is also made to tackle subjective (qualitative) and objective (quantitative) evaluation information simultaneously, towards effective decision making.

Supplier selection is a key strategic concern for the large-scale organizations. In view of this, a novel decision support framework is proposed to address g-resilient (green and resilient) supplier selection issues. Green capability of suppliers' ensures the pollution free operation; while, resiliency deals with unexpected system disruptions. A comparative analysis of the results is also carried out by applying well-known decision making approaches like Fuzzy-TOPSIS and Fuzzy-VIKOR.

In relation to 3PL service provider selection, this dissertation proposes a novel 'Dominance-Based' model in combination with grey set theory to deal with 3PL provider selection, considering linguistic preferences of the Decision-Makers (DMs). An empirical case study is articulated to demonstrate application potential of the proposed model. The results, obtained thereof, have been compared to that of grey-TOPSIS approach.

Another part of this dissertation is to provide an integrated framework in order to assess g-resilient (ecosilient) performance of the supply chain of a case automotive company. The overall g-resilient supply chain performance is determined by computing a unique ecosilient (g-resilient) index. The concepts of Fuzzy Performance Importance Index (FPII) along with

Degree of Similarity (DOS) (obtained from fuzzy set theory) are applied to rank different g-resilient criteria in accordance to their current status of performance.

The study is further extended to analyze, and thereby, to mitigate various risk factors (risk sources) involved in e-commerce exercises. A total forty eight major e-commerce risks are recognized and evaluated in a decision making perspective by utilizing the knowledge acquired from the fuzzy set theory. Risk is evaluated as a product of two risk quantifying parameters viz. (i) Likelihood of occurrence and, (ii) Impact. Aforesaid two risk quantifying parameters are assessed in a subjective manner (linguistic human judgment), rather than exploring probabilistic approach of risk analysis. The 'crisp risk extent' corresponding to various risk factors are figured out through the proposed fuzzy risk analysis approach. The risk factor possessing high 'crisp risk extent' score is said be more critical for the current problem context (toward e-commerce success). Risks are now categorized into different levels of severity (adverse consequences) (i.e. negligible, minor, marginal, critical and catastrophic). Amongst forty eight risk sources, top five risk sources which are supposed to adversely affect the company's e-commerce performance are recognized through such categorization. The overall risk extent is determined by aggregating individual risks (under 'critical' level of severity) using Fuzzy Inference System (FIS). Interpretive Structural Modeling (ISM) is then used to obtain structural relationship amongst aforementioned five risk sources. An appropriate action requirement plan is also suggested, to control and minimize risks associated with e-commerce exercises.

***Keywords:*** ***Decision Support System (DSS), Fuzzy Set Theory (FST), Grey Set Theory, Fuzzy-PROMETHEE, Fuzzy-TODIM, Fuzzy-TOPSIS, Fuzzy-VIKOR, Grey-TODIM, Interpretive Structural Modeling (ISM), Robot Selection, Supplier Selection, 3PL Service Provider, Fuzzy Performance Importance Index (FPII), Degree of Similarity (DOS).***

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# Abbreviations

| | |
|---|---|
| 3PL | Third Party Logistics |
| 3PRL | Third Party Reverse Logistics |
| ABC | Activity-Based Costing |
| AHP | Analytical Hierarch Process |
| ANP | Analytical Network Process |
| DEA | Data Envelopment Analysis |
| DEMATEL | Decision Making Trial and Evaluation Laboratory |
| DM | Decision-Maker |
| DOS | Degree of Similarity |
| DSS | Decision Support System |
| EC | Electronic Commerce |
| FDSS | Fuzzy Decision Support System |
| FIS | Fuzzy Inference System |
| FPPI | Fuzzy Performance Importance Index |
| FST | Fuzzy Set Theory |
| GRA | Grey Relation Analysis |
| GSCM | Green Supply Chain Management |
| ISM | Interpretive Structural Modeling |
| LSP | Logistics Service Provider |
| MADM | Multi-Attribute Decision Making |
| MCDM | Multi-Criteria Decision Making |
| MOORA | Multi-Objective Optimization on the basis of Ratio Analysis |
| PROMETHEE | Preference Ranking Organization METHod for Enrichment Evaluations |
| SCM | Supply Chain Management |
| SCRM | Supply Chain Risk Management |
| TODIM | Tomada de Decisión Inerativa Multicritero |
| TOPSIS | Technique for Order Preference by Similarity to Ideal Solution |
| VIKOR | VIsekriterijumsko KOmpro-Misno Rangiranje |

# Chapter 1

# Introduction

## 1.1 Decision Making

Decision making is a cognitive process used to identify the best and the worst choice amongst a set of given alternatives. It can also be viewed as an intellectual course of action performed frequently to determine the best alternative amongst available candidate alternatives with respect to a particular/certain set of criterion/criteria. Carroll and Johnson (1990) defined the decision making as a process by which a person, group or an organization identifies a choice or judgment to be made, gathers and evaluates information about alternatives and selects the best among the alternatives. Strategic decision making is an internal part of the organizations and is implemented to ensure smooth functioning of the business in order to achieve various organizational goals.

In industrial context, decision making is a process by which managers can effectively respond threats and opportunities to enhance the organizational performance along with successful execution of business goals. Such kind of decision making concept involves several activities like goal determination, problem formulation, alternatives identification and evaluation or selection (Schwenk, 1984). All the managerial functions such as planning, organizing, directing, and controlling can be fulfilled through decisions taken by the managers or Decision-Makers (DMs). The role of DMs is extremely important in the context of decision making; as they provide all the input information (or judgment); and finally, to develop a realistic solution.

Satty (2008) stated that people do act like a Decision-Maker fundamentally in their daily routine life and anything they do consciously or unconsciously is the result of some sort of decision. Decision making can be tough or even unpleasant and can result conflict sometimes. The challenging part is to prefer one solution where the positive outcomes may compensate possible losses.

A general decision making process can be divided into the following steps (Baker et al., 2002; Fülöp, 2005):

i) Define the problem
ii) Establish goals
iii) Identify alternatives
iv) Define a set of criteria
v) Select a decision making tool
vi) Evaluate alternatives against a set of criteria
vii) Validate solutions against problem statement

Decision Making is a broad concept that comes into picture in many diverse circumstances. In this dissertation, the following focus areas have been attempted in perspectives of industrial decision making:

a) Selection of industrial robot
b) G-resilient supplier selection
c) Selection of third party logistics (3PL) service provider
d) Performance assessment of g-resilient supply chain and,
e) E-commerce risk assessment

## 1.2 Single Criterion Decision Making Versus Multi-Criteria Decision Making

Decision making approach that deals with the single attribute/criterion only, is known as the single criterion decision making. Traditional single criteria decision making methodology is generally focused to the maximization of the benefit and minimization of the cost (Pohekar and Ramachandran 2004). Long before, decisions were made frequently only on the basis of a single criterion like profit or cost. However, often cost or profit alone does not completely capture the desirability of a decision alternative. Due to absence of criteria conflict, single criterion decision making appears simple and can be performed easily. Whilst problem arises in case of multiple criteria decision making in which criteria may be contradicting to each other (in terms of requirement). For instance, cost may conflict with profit; the former being Lower-is-Better (LB) and the later being Higher-is-Better (HB). Thus the Multi-Criteria Decision Making (MCDM) becomes one of the important and essential tool to analyze real life complex decision making problems because of their intrinsic capability to evaluate different alternatives against numerous criteria for the possible selection of appropriate strategy /policy /scenario /alternatives. The selected alternatives must be explored in-depth before their final implementation. According to (Xu and Yang, 2001) MCDM problems are common in everyday life and refers to decision making in the presence of multiple, usually conflicting, criteria. A comprehensive multi-criteria decision making tree is shown in Fig. 1.1.

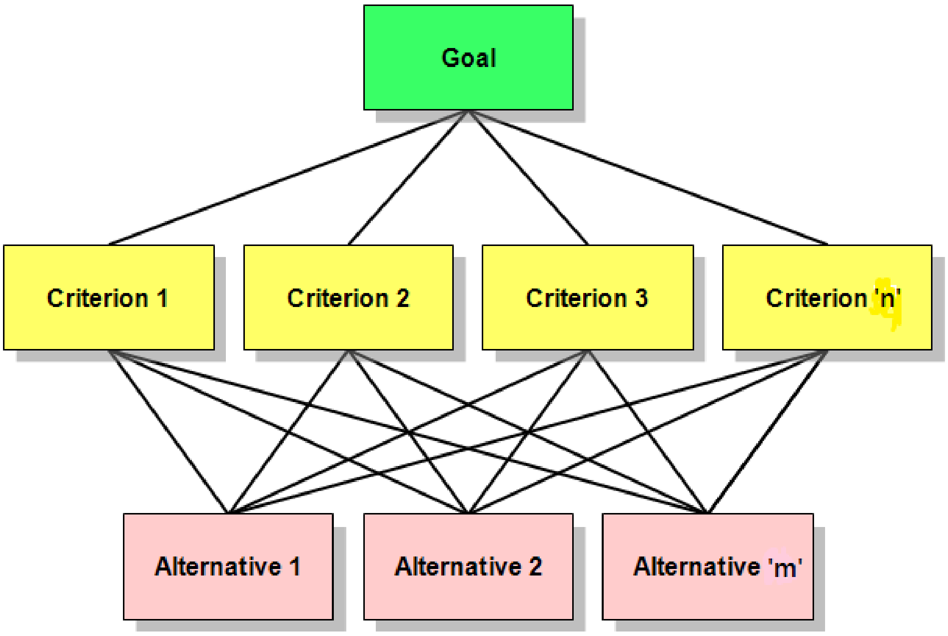


Fig. 1.1: Multi-Criteria decision making tree.

Triantaphyllou et al. (1998) mentioned that multi-criteria decision making is a branch of a general class of Operations Research (OR) models devoted for the development of decision support tools and methodologies to address complex problems involving multiple criteria/goals or objectives of conflicting nature. This major class of method (i.e. MCDM) is further divided into two categories viz. Multi-Attribute Decision Making (MADM) and Multi-Objective Decision Making (MODM). MADM concentrates on problems with discrete decision spaces while; MODM is focused on the decision problems, where decision space is continuous (Fig. 1.2).

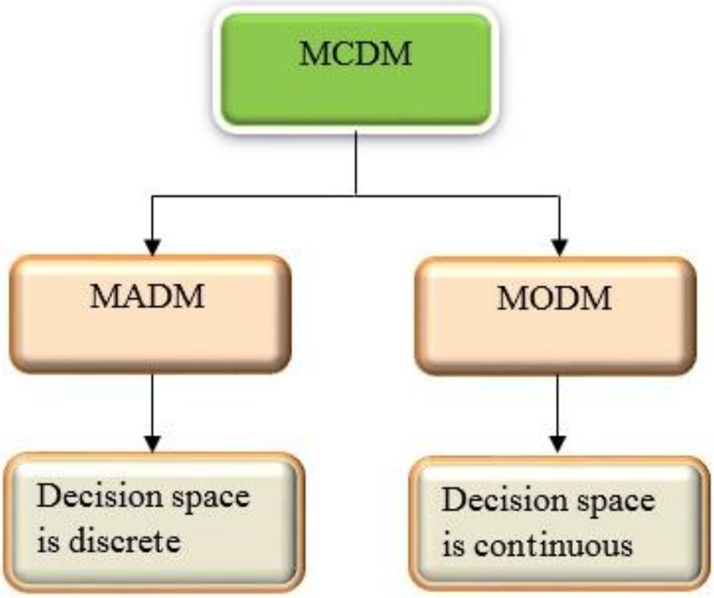


Fig. 1.2: Categorization of MCDM problems

## 1.3 Decision Making Data

Decision making data are of two types (Fig. 1.3): quantitative (i.e. objective) and qualitative (i.e. subjective)

i) **Quantitative data** is a numerical measurement expressed in terms of numbers instead of a natural language description. Quantitative data can be expressed as a number, or in a quantified value. There are two types of quantitative data notified viz. discrete data and continuous data. Discrete data can only take specific mathematical values: e.g. load capacity of a robot etc.; whereas, continuous data can take any numerical value like velocity of a moving object, height, mass, length etc.

ii) **Qualitative data** is a categorical measurement expressed not in terms of numbers, but rather by means of a natural language description. This type of data consists of words and narratives (linguistic preferences). Qualitative data is basically the criteria information as evaluated through human judgment expressed in linguistic terms. Some examples of qualitative data are like service quality, reliability, man–machine interface, flexibility, textures, smells, tastes etc.

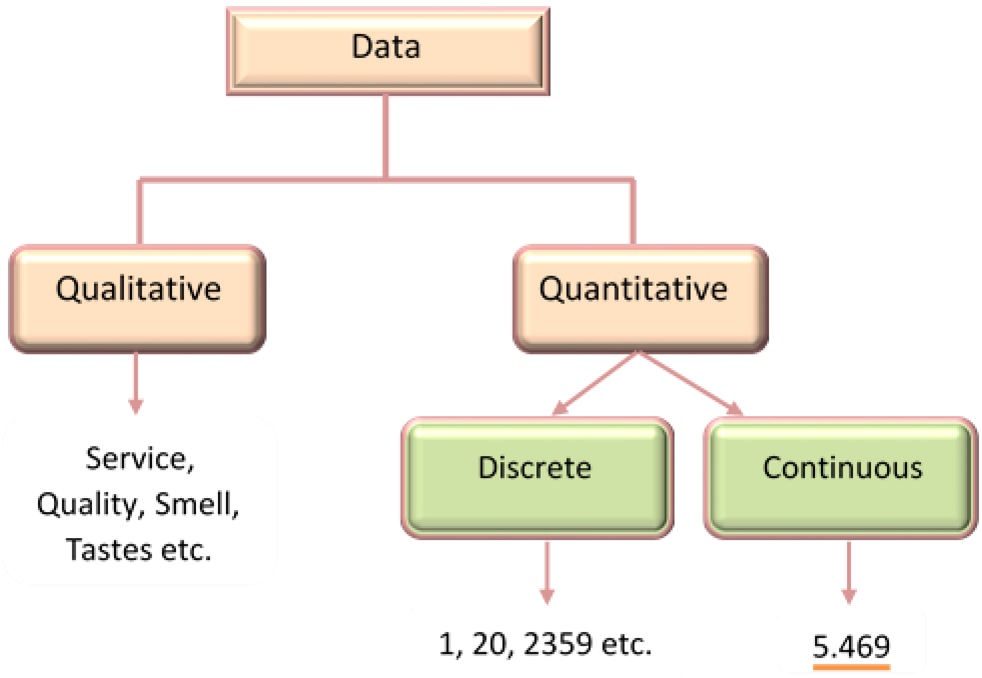

Fig. 1.3. Types of decision making data

## 1.4 Traditional Decision Making Approaches: An Overview

A number of decision making approaches has been developed till now and applied in various domains to establish a rational decision. Traditional/conventional decision making approaches usually operate under quantitative data. Some of the most cited traditional decision making approaches have been discussed below.

### a) TODIM (Tomada de Decisión Inerativa Multicritero)

TODIM (Tomada de Decisión Inerativa Multicritero), an acronym in Portuguese of Interactive and Multi-Criteria Decision Making method first developed and utilized by (Gomes and Lima, 1991) for ranking of projects in consideration with environmental impacts. Application of TODIM could be further found in (Gomes and Rangel, 2009; Gomes et al., 2009; Gomes et al., 2013) for rental evaluation of residential properties, analysis of natural gas destination selection etc.

### b) COPRAS

The COPRAS (COmplex PRoportional ASsessment) is a MCDM approach proposed by (Zavadskas et al., 1996). The method was widely used to solve various decision making problems in construction, property management, economics etc. Application of COPRAS method could be seen in (Chatterjee et al., 2011) for materials selection, (Zavadskas et al., 2007) for road design assessments, (Andruškevicius, 2005) for solving contractor assessment problem.

### c) TOPSIS

Hwang and Yoon (1981) introduced TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) based on the idea that the best alternative should have the shortest distance from the ideal solution and the farthest distance from the anti-ideal solution. Based on two distance measures, a closeness coefficient (also called relative closeness) is determined. Alternatives are then ranked based on their closeness coefficient values. Applications of TOPSIS could be obtained in (Parkan and Wu, 1999; Shanian and Savadogo, 2006; Lai et al., 1994; Sarkar, 2013).

### d) VIKOR

The VIKOR whose Serbian name is ‘VIsekriterijumsko KOmpro-Misno Rangiranje,’ means Multi-Criteria Optimization (MCO) and compromise solution. The foundation for such a compromise solution was established by (Yu, 1973) and (Zeleny, 1982); and, later promoted by (Opricovic and Tzeng, 2004). It focuses on ranking and selecting the best alternative from a finite set of alternatives with conflicting criteria; and thus to propose the compromise solution (one or more). Application of VIKOR based MCDM approaches could be found in literature (Chatterjee et al. 2010; Jahan et al., 2011; Cristóbal, 2011) for selection of industrial robots, material selection, selection of a renewable energy project, respectively.

### e) PROMETHEE

The PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) is a preference function based interactive multi-criteria decision making approach first developed by (Brans and Vincke, 1985). The PROMETHEE I method can provide partial ordering of the decision alternatives; whereas, PROMETHEE II method can derive the full ranking order of the candidate alternatives. Detailed illustration of this method could be found in (De Keyser and Peeters, 1996; Safari et al., 2012).

## f) MOORA

MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) was first introduced by (Brauers and Zavadskas, 2006). Multi-objective optimization problems can be found in various fields wherever optimal decisions need to be taken in presence of trade-offs between two or more conflicting objectives/criteria like product and process design, finance, aircraft design, oil and gas industry, manufacturing sector, automobile design. Applications could be found in literature (Brauers, 2008; Brauers, et al. 2008; Karande and Chakraborty, 2012) for contractor's ranking, decision making for road design and materials selection, respectively.

## g) Weighted Sum Method (WSM)

The weighted sum model (WSM) (Triantaphyllou and Mann, 1989) is probably the most commonly used approach, especially in single dimensional problems. If there are $m$ alternatives and $n$ criteria then, the best alternative is the one that satisfies the following expression

$$A^*_{wsm} = Max\sum_{i}^{j} a_{ij} * w_j \qquad i = 1,2,3,\ldots,m \tag{1.1}$$

Here, $A^*_{wsm}$ is the weighted sum score of the best alternative, $n$ is the number of decision criteria, $a_{ij}$ is the actual value of the $i^{th}$ alternative in terms of the $j^{th}$ criterion, and $w_j$ is the weight of importance of the $j^{th}$ criterion. The assumption that governs this model is the additive utility assumption. That is, the total value of each alternative is equal to the sum of products given as Eq. 1.1. In single-dimensional cases, in which all the units are the same (e.g., dollars, feet, seconds), the WSM can be used without difficulty. Difficulty with this method emerges when it is applied to multi-dimensional decision-making problems. Then, in combining different dimensions, and consequently different units, the additive utility assumption is violated and the result is equivalent to adding apples and oranges (Triantaphyllou et al. 1998, Triantaphyllou, 2000; Mateo, 2012).

## h) Weighted Product Model (WPM)

The weighted Product Model (WPM) (Triantaphyllou and Mann, 1989) is very similar to the WSM. The main difference is that instead of addition in the model there is multiplication. Each alternative is compared with the others by multiplying a number of ratios, one for each criterion. Each ration is raised to the power equivalent to the relative weight of the corresponding criterion. In general, in order to compare two alternatives $A_k$ and $A_l$, the following product is obtained

$$R\left(\frac{A_k}{A_l}\right) = \prod_{j=1}^{n}\left(\frac{a_{kj}}{a_{lj}}\right)^{w_j} \tag{1.2}$$

Where $n$ is the number of criteria, $a_{ij}$ is the actual value of the $i^{th}$ alternative in terms of the $j^{th}$ criterion, and $w_j$ is the weight of importance of the $j^{th}$ criterion. If $R\left(\frac{A_k}{A_l}\right)$ is greater than or equal to one, then it indicates that alternative $A_k$ is more desirable than alternative $A_l$ (in the maximization case). The best alternative is the one that is better than or at least equal to all other alternatives (Triantaphyllou, 1998; Mateo, 2012)

## i) ELECTRE

ELECTRE is a family of MCDA methods that originated in Europe in the mid-1960s. The acronym ELECTRE stands for "ELimination Et Choix Traduisant la REalité". The method was first proposed by Roy (1991) and initially designed to work on real world choice problems of firms (rarely mono criterion founded) and to permit to decision makers to go beyond the classic Weighted Sum Method. Nowadays, ELECTRE method is more widely known and has evolved into several expansions and utilizations (Hatami-Marbini and Tavana, 2011; Botti and Peypoch 2013). The basic concept of the ELECTRE method is to deal with "outranking relations" by using pairwise comparisons among alternatives under each one of the criteria separately. The outranking relationship of the two alternatives Ai and Aj describes that even when the $i^{th}$ alternative does not determine the $j^{th}$ alternative quantitatively, then the decision maker may still take the risk of regarding Ai as almost better than Aj. Alternatives are said to be dominated, if there is another alternative which excels them in one or more criteria and equals in the remaining criteria (Buchanan et al., 1998; de Almeida, 2007; Sevkli, 2010).

## 1.5 Decision Making in Presence of Subjective Data: Problems and Challenges

In real world, most of the evaluation criteria are described in a subjective manner (ill-defined) and are characterized by ambiguity (multi-possibility) and vagueness. Thus, capability of traditional decision making techniques (those deal with quantitative data) are always criticized. Most of the decisions taken are based on the assessment of number of alternatives against a certain set of criteria. This procedure becomes more difficult if the criteria are expressed in subjective terms (linguistic preferences). This is because subjective criteria values are difficult to quantify (Triantaphyllou, 1995). There is no methodology or tool available to operate in the context of complex and dynamic interactive system incorporating both quantitative and qualitative data in real life industrial decision making scenario. During decision making, the subjective data cannot be analyzed by standard statistical methods, either because there are numerous missing records, or because the data are in the form of qualitative rather than quantitative measures. In many cases, the information contained in these databases is undervalued and underutilized because the data cannot be easily assessed or analyzed. In this context, fuzzy set theory provides a useful tool to deal with problems in which the attributes and phenomena are imprecise and vague in nature (Zadeh, 1965).

## 1.6 Application Potential of Fuzzy and Grey Numbers Set Theories

Recent years have witnessed considerable efforts on discovering fuzzy application, aiming to cope up with fuzziness in knowledge representation and decision support process. Therefore, the necessity of applying fuzzy logic in data analysis is due to the following (Yanfang and Fu, 2008):

a) Fuzziness is inherent in many problems of knowledge representation. Complex decision processes often deal with generalized concepts and linguistic expressions which are generally fuzzy in nature.

b) Moreover, fuzziness may prevail in many other association cases in which impression, matching, similarity, implication, partial truth or the like is present.

c) The modeling of imprecise and qualitative knowledge, as well as the transmission and handling of uncertainty at various stages, are possible through the use of fuzzy sets.

d) Fuzzy logic is capable of supporting to a reasonable extent, human type reasoning in natural form.

In the context of industrial decision making, most of the criteria being qualitative in nature; the extent of successful performance (appropriateness) of each criterion is judged by the experts (also called Decision-Makers, DMs). Expert judgment which may vary depending on individuals' perception as well as viewpoint. Moreover, it becomes difficult for the DMs to assign exact numeric score against performance rating of various subjective criteria-attributes. The degree of importance (priority weights) of various criteria also differs due to individuals' discretion. This kind of uncertainty in decision making process can fruitfully be tackled by using fuzzy logic. In exploration of fuzzy set theory in group decision making process, DMs personal opinion is expressed by linguistic variables which are further converted into appropriate fuzzy numbers. With the help of fuzzy arithmetic operations, aggregated criteria weight and corresponding criteria rating are combined and finally analyzed to compute an overall assessment index; based on which the most appropriate alternative is selected amongst available candidate alternatives. Basic fuzzy preliminaries could be well articulated from (Zadeh 1974; Zadeh, 1975; Kauffman and Gupta, 1991; Zimmermann, 1991; Chen and Chen, 2003; Wei and Chen 2009; Liu and Wang, 2011).

Apart from fuzzy logic, grey numbers set theory (Ju-Long, 1982), developed by Prof. Deng in 1982, has become an effective decision making method under discrete data and incomplete information. Similar to fuzzy set theory, it is felt that grey numbers set theory (Yang and Li, 2011; Liu et al., 2012) can also be used to facilitate a variety of decision making problem solutions. Grey set theory uses a specific concept of information. In grey theory, a system whose information is completely known is appeared as a 'white' and, a system whose information is completely unknown is appeared as a 'black'; however, a system whose information is partly known or partly unknown is entitled as a 'grey' system. Meanwhile, it has been observed that the real world decision making problems may be partially known or partially unknown (i.e. vague and ambiguous); therefore, grey numbers set theory can be useful in this regard. Indeterminate subjective verdict given by the DMs is hardly possible to assess in terms of exact mathematical principles; thus, exploration of grey theory may be evidenced fruitfully to tackle uncertainty as well as imprecision of subjective human judgment. In fact inadequate information is the basic characteristic of the problems measured in grey systems theory (Lin et al., 2004). Jadidi et al. (2009) also stated that grey theory is one of the new mathematical methods and can be used successfully to analyze systems with uncertain and incomplete information. As of now, Grey theory has been applied in various domains like forecasting, computer graphics, decision-making system control etc. as found in existing literature resource (Li et al., 2007a; Jadidi et al., 2009; Bai and Sarkis, 2010a; Wen, 2011; Rahimnia et al., 2011; Manzardo et al., 2012; Kose et al., 2013; Oztaysi, 2014; Dang et al., 2007; Chen and Liu, 2008; Zavadskas et al., 2010; Golmohammadi and Mellat-Parast, 2012; Kuang et al., 2015).

## 1.7 Organization of the Present Dissertation

The present dissertation has been organized into eight different chapters. Brief outline of each chapter has been provided below:

**Chapter 1 (Introduction)**: In this chapter, a detailed introduction on basic concepts of decision making has been delineated. Scenarios of decision making in consideration with single criterion and multiple criteria (Multi-Criteria Decision Making; MCDM) along with classification of decision making data (objective and subjective data) have been discussed. This chapter has been made enriched with the brief discussion on traditional MCDM approaches like TODIM, COPRAS, TOPSIS, VIKOR, PROMETHEE and MOORA. Owing to the ambiguity and vagueness associated with subjective decision information, the application potential of fuzzy/ grey numbers set theory has been mentioned herein. The problems and challenges generally faced in industrial decision making situations involving subjective data have been illustrated in detail.

**Chapter 2 (Literature Review)**: This chapter has articulated outcome of the past research on various decision making domains like selection of industrial robots, supplier selection (green, sustainable, resilient supplier selection etc.), and 3PL service provider selection etc. To take care of vague and ambiguous selection criteria, and the information obtained thereof; this chapter has further highlighted the necessity of conceptualizing an efficient decision support framework in order to evaluate and finally to rank the alternatives by utilizing subjective judgment of the Decision-Makers (DMs). Moreover, this chapter has summarized the work attempted by previous researchers on various aspects of decision making towards performance assessment of supply chains (viz. traditional supply chain, green supply chain, resilient supply chain etc.). Additionally, this chapter has illustrated the survey of past literature on risk assessment in industrial context (viz. supply chain risk, suppliers' risk, e-commerce risk etc.). Based on the extensive understanding on prior state of art, the existing research gaps have been identified and specific objectives of the present dissertation have been pointed out.

**Chapter 3 (Selection of Industrial Robot)**: This chapter has explored various decision support systems for industrial robot selection. The chapter has applied (i) Fuzzy-TODIM, (ii) Grey-TODIM and, iii) Extended (Fuzzy) PROMETHEE to identify the best and the worst choice from amongst the set of candidate robots, for a particular industrial application. Use of fuzzy set theory as well as grey set theory has been attempted in this chapter to tackle inherent drawbacks (subjectivity) involved in the human judgment fruitfully.

**Chapter 4 (A New TODIM-Based Decision Support Framework for G-Resilient Supplier Selection in Fuzzy Environment)**: In this chapter, the concept of 'g-resilient' supplier has been introduced to suit modern supply chain management. The integration of 'green' as well as 'resilient' supplier selection criteria has been carried out for effective evaluation and selection of an appropriate supplier alternative. A novel decision support framework has been developed and conceptualized through an empirical study towards g-resilient supplier selection. The results obtained thereof, have been compared to that of fuzzy-TOPSIS and fuzzy-VIKOR. The concept of a unique performance index (called g-resilient index) has been proposed herein to facilitate supplier selection issues.

**Chapter 5 (A Novel Decision Support Framework for Selection of 3PL Service Providers: A Dominance-Based Approach in Combination with Grey Set Theory)**: This chapter has provided outcome of a case empirical study on 3PL service provider selection. A new 'dominance based' decision support framework in conjugation with grey set theory has been proposed herein. In order to examine application potential of the proposed approach, result obtained thereof, has been compared to that of grey-TOPSIS. Comparative results have showed feasibility of the proposed DSS towards solving intricate decision making problems.

**Chapter 6 (Evaluation of Supply Chain's G-Resilient Performance Index: A Fuzzy Embedded Decision Support Framework)**: This chapter has focused on the performance assessment of g-resilient (i.e. green + resilient) supply chain. A case automotive company located at the southern part of India has been considered as a part of this empirical study. A decision support system embedded with fuzzy numbers set theory has been utilized to measure the supply chain's 'g-resilient' (also called 'ecosilient') index in relation to the said automotive company. The DSS applied in this chapter has explored Fuzzy Set Theory (FST), the concept of fuzzy Degree of Similarity (DOS) as well as the Fuzzy Performance Importance Index (FPII). An Interpretive Structural Modeling (ISM) approach has also been attempted to explore the interdependency/ interrelationship amongst green and resilient criteria for evaluating g-resilient performance of the automotive company's supply chain.

**Chapter 7 (E-Commerce Risk Assessment: A Fuzzy Decision Making Perspective)**: This chapter has provided the necessity of assessing and mitigating risks in company's e-commerce exercises. Risk has been represented herein as a function of two parameters: likelihood/ probability of occurrence as well as impact (consequence of occurrence). The application of fuzzy risk analysis has been carried out to measure the risk extent against individual risk sources. Based on their 'crisp risk extent', the risk sources have been categorized into different levels of severity. An ISM approach has also been attempted to explore the interdependency amongst various e-commerce risks possessing high degree of severity towards the occurrence of e-commerce failure (adverse consequences). Specific guidelines have also been recommended to assess, monitor, control and to mitigate various e-commerce risks.

**Chapter 8 (Summary and Conclusions)**: This chapter has provided executive summary of the entire work carried out in this dissertation and has highlighted specific contributions to the extent body of past research in the context of industrial decision making scenario. Limitations of the present work have also been pointed out with reference to the future scope of work.

## Chapter 2

# Literature Review

## 2.1 Selection of Industrial Robots

The word ‘robot’ was conceived by a Czech author K. Capeak in 1920, and it came from the word ‘robota’, which means ‘worker’. A robot can be defined as a multi-functional operator, which can be controlled by programs (Mondal and Chakraborty, 2013). As defined by (Rao et al., 2011), robots are ‘automatically controlled, reprogrammable, multi-purpose manipulators programmable in three or more axes. As described by (Chatterjee et al., 2010), an industrial robot is a general purpose, reprogrammable machine with certain anthropometrical features.

Recently, the developments in information technology and engineering have been the main stimulant for the increased utilization of robots in a variety of advanced manufacturing processes. Robots with different capabilities and specifications are readily available for a wide range of applications and can easily be programmed to keep a constant speed and the desired quality when performing a task repetitively. Robots are capable of performing repetitious, difficult, and hazardous tasks with high precision, and can effectively improve quality as well as productivity, if applied properly. Therefore, manufacturers are preferring to utilize robots in various industrial applications where repetitive, difficult or hazardous tasks need to be performed for diverse industrial applications, including material handling, assembly, finishing, machine loading, spray painting and welding (Kumar and Garg, 2010; Chatterjee et al., 2010).

In order to improve product quality and to enhance the productivity, application of robots in various manufacturing units has always been a key concern. Robot selection is one of the critical decision making tasks frequently performed by various industries in order to choose the best suited robot for specific industrial purposes. In recent marketplace, the number of robot manufacturers has increased remarkably offering a wide range of models and specifications; thus, robot selection has become indeed confusing as well as complicated. It has become much more complicated due to increased complexity, advanced features and facilities that are continuously being incorporated into the robots by different manufacturers (Chatterjee et al. 2010).

As improper selection of robots may adversely affect company's competitiveness in terms of the productivity as well as quality loss (Rao et al. 2011), Decision-Makers (DMs) need to consider subjective and objective robot selection attributes both irrespective of their nature (i.e beneficial or cost). Meanwhile, inculcation of various subjective and objective criteria/attributes towards selection of industrial robots are making the process more difficult. Selection of an appropriate robot is a sensitive process; it may result massive letdown, if not chosen properly; therefore, in past few years many researchers explored the robot selection problem which include the applications of Multi-Criteria Decision Making (MCDM) methods, production system performance optimization models, computer-assisted models and statistical models (Chatterjee et al., 2010).

The extent body of existing literature is found quite rich in concerning robot selection problem from past few decades. Researchers, engineers, scientists and robotics' experts all over the globe emphasized on different aspects of robotic system that included the selection of robots, design of controllers, robotic arms, manipulators, types of mechanisms used in robots and selection of grippers/end effectors etc. Goh et al. (1996) presented a revised weighted sum model that incorporated the values assigned by a group of experts on different evaluation factors in selecting robots. Zhao et al. (1996) introduced Genetic Algorithm (GA) for optimal Robot Selection and Workstation Assignment (RS/WA) problem for a Computer Integrated Manufacturing (CIM) system. A multi-chromosome GA combined with heuristic bin packing algorithm was implemented for solving the said problem.

Goh (1997) provided a robot selection model that incorporated the inputs from multiple Decision-Makers (DMs). This model was based on the Analytic Hierarchy Process (AHP) in consideration with both subjective and objective robot selection criteria. Parkan and Wu (1999) demonstrated exploration aspects of Multi-Attribute Decision Making (MADM) and performance measurement methods through a robots selection problem. Particular emphasis was placed on a performance measurement procedure called OCRA (Operational Competitiveness Rating) and an exploration of a MADM tool called TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). A rank correlation test showed that the methods produced similar ranking orders for the robots. The final selection was made on the basis of the rankings obtained by averaging the results of OCRA, TOPSIS, and a utility model.

Braglia and Petroni (1999) proposed a methodology for the selection of industrial robots using Data Envelopment Analysis (DEA). It aimed at the identification, in a cost/benefit perspective, of the optimal robot, by measuring, for each robot, the relative efficiency through the resolution of linear programming problems. The methodology was based on a sequential dual use of DEA with restricted weights. This approach increased the discriminatory power of standard DEA and made it possible to achieve a better balancing of robot performances. Chu and Lin (2003) proposed a fuzzy-TOPSIS based hybrid approach for robot selection. Ratings of various alternatives and subjective criteria with their corresponding weight were judged in linguistic terminology represented by fuzzy numbers. To ensure the harmonious relationship between the objective and the subjective attributes; objective criteria were transformed into dimensionless indices first. Further, the ranking order of robot alternative was provided according to their closeness coefficient score in descending order.

Bhangale et al. (2004) attempted to generate and maintain reliable as well as exhaustive database of robot manipulators based on their different pertinent attributes. This database could be used to standardize the robot selection procedure for a particular operation. The robot selection procedure allowed rapid convergence from a very large number of candidate robots to a manageable shortlist of potentially suitable robots using elimination search based on the few critical selection attributes. Subsequently, the selection procedure proceeded to rank the alternatives in the shortlist by employing different attributes based specification methods and graphical methods. The ranks of the candidate robots were calculated with respect to the best possible robot, i.e. 'positive benchmark robot', for a particular application. Bhattacharya et al. (2005) delineated Analytical Hierarchy Process (AHP) with Quality Function Deployment (QFD) for robot selection under requirement perspective. Seven technical factors (drive system, geometrical dexterity, path measuring system, robot size, material of robot, weight of robot, initial operating cost etc.) required for robot selection were recognized for the case study. Cost factor measures (acquisition cost of robot, cost of robot gripper mechanisms, cost of sensors, total cost of layout necessary for installation of robot, cost of feeders, maintenance cost and cost of energy) were amalgamated in the suggested hybrid AHP/QFD model to find out the necessities for robotic system employment in a manufacturing firm from an economic point of view.

Kapoor and Tak (2005) proposed a methodology for solving common robot selection problems using a modified AHP by incorporating ‘Fuzzy Linguistic Variables’ in place of real numbers. The methodology encapsulated creation of Fuzzy Interface for conversion of input and output variables into suitable linguistic variables. Further, employing the fuzzification process by assigning the linguistic variables to numerical values of the membership functions and formulating suitable decision rules, the procedure culminated into the defuzzification process for converting fuzzy output into crisp value and obtained the result in the form of Fuzzy Score. Rao and Padmanabhan (2006) developed a methodology based on digraph and matrix methods for evaluation of alternative industrial robots. A robot selection index was proposed that evaluated and ranked robots for a given industrial application.

Jolly et al. (2007) proposed a two-stage approach using Artificial Neural Networks (ANN) for the intelligent decision making by the robots in a MiroSot small league. The first stage involved the use of an evolutionary algorithm for getting a rough estimate of the neural network weight matrices. The approach was then generalized to the case of quick, intelligent and accurate decision making in the case of a robot soccer system with robots utilizing the concept of compounded artificial neural networks. In this approach, a soccer field was divided into three zones so that the decision of the robots depended on the zone of the ball at any instant. The concept of a forward robot was also introduced in this paper to enhance the accuracy of the decision making task with the global strategy of advancing towards the goal area of the opponent for scoring a goal.

Chatterjee et al. (2010) attempted to solve the robot selection problem using two most appropriate Multi-Criteria Decision Making (MCDM) methods and compared their relative performance for a given industrial application. The first MCDM approach was ‘VIsekriterijumsko KOmpromisno Rangiranje’ (VIKOR), a compromise ranking method and the other one was ‘ELimination and Et Choice Translating REality’ (ELECTRE), an outranking method. Two real time examples were cited in order to demonstrate as well as to validate the applicability and potentiality of these MCDM methods. It was observed that the relative rankings of the alternative robots as obtained using these two MCDM methods matched quite well with those as derived by the past researchers. Kumar and Garg (2010) developed a deterministic quantitative model based on Distance Based Approach (DBA) method for evaluation, selection and ranking of the alternative robots. Authors further, performed sensitivity analysis to investigate the critical and non-critical performance attributes for a robot.

Martin-Ramos et al. (2010) presented a technique that enabled the best paths to be selected from among a set provided by a probabilistic planning method ‘Rapidly Exploring Random Trees’ (RRT) for tackling the problem involved in generating manoeuvres in robots with nonholonomic restrictions. The application of MCDM techniques (generation and ranking) enabled the development of an automatic tool for finding the best manoeuvres for nonholonomic robots. Jolly et al. (2010) proposed an intelligent task planning and action selection mechanism for a mobile robot in a robot soccer system through a fuzzy neural network approach. Rao et al. (2011) proposed a subjective and objective integrated multiple attribute decision making method for the purpose of robot selection. The method considered the objective weights of importance of the attributes as well as the subjective preferences of the Decision-makers to decide the integrated weights of importance of the attributes. Furthermore, the method used fuzzy logic to convert the qualitative attributes into the quantitative attributes.

Devi (2011) extended the VIKOR method in intuitionistic fuzzy environment, aiming at solving multi-criteria decision making problems of robot selection. In this approach, the weights of criteria and ratings of alternatives were taken as triangular intuitionistic fuzzy set. This study presented a robot selection problem for material handling task. Kentli and Kar (2011) presented a multi-criteria decision making model for a robot selection problem. The proposed model used satisfaction function to convert various robot attributes into a unified scale. Further, a distance measure technique was used to ascertain the highest ranked candidate robot. Koulouriotis and Ketipi (2011) suggested a fuzzy digraph method for robot evaluation and selection according to a given industrial application. The entire information about the objective and subjective attributes were articulated in linguistic terms, shown by fuzzy numbers. The suggested approach was applied by converting the fuzzy output into a crisp value and estimating the selection index. Özgürler et al. (2011) solved a robot selection problem for material handling task in a flexible manufacturing system. Two MCDM methods viz. AHP and TOPSIS were used to select the most convenient robot among a given set of alternatives for a given industrial application.

Taillandier and Stinckwich (2011) attempted to define the exploration strategies for rescue robots using the PROMETHEE Multi-Criteria Decision Making Method. This problem was found having many applications and, among them, the post-disaster search of victims in an urban space. The PROMETHEE II method allowed establishing a complete ranking between possible movements based on outranking relations. Experimental results showed that this approach could be used to effectively combine different criteria and outperform several classic exploration strategies. Karsak et al. (2012) presented a decision model based on fuzzy linear regression for industrial robot selection. Fuzzy linear regression was found as an alternative approach to statistical regression for modeling situations where the relationships could be vague or the data set could not satisfy the assumptions of statistical regression.

Chaghooshi et al. (2012) applied an efficient method for industrial robotic system selection. In this paper, the weights of various criteria were calculated using fuzzy Shannon's Entropy. After that, fuzzy-TOPSIS was utilized to rank the alternatives. The authors compared the result of fuzzy-TOPSIS with fuzzy-VIKOR method. Iç et al. (2013) developed a two-phase robot selection decision support system, namely ROBSEL in order to help the Decision-Makers in their robot selection decisions. In development of ROBSEL, an independent set of criteria was obtained first and arranged in the Fuzzy Analytical Hierarchy Process (FAHP) decision hierarchy. In the first elimination phase of the decision support system, the user obtained the feasible set of robots by providing limited values for a set of requirements. ROBSEL; then, used FAHP decision hierarchy to rank the feasible robots in the second phase.

Mondal and Chakraborty (2013) applied four models of Data Envelopment Analysis (DEA), i.e. Charnes, Cooper and Rhodes (CCR), Banker, Charnes and Cooper (BCC), additive, and cone-ratio models in order to identify the feasible robots having the optimal performance measures, simultaneously, satisfying the organizational objectives with respect to cost and process optimization. Furthermore, the weighted overall efficiency ranking method of multi-attribute decision making theory was also employed for arriving at the best robot selection decision from the short-listed competent alternatives. Bai and Wang (2013) developed a Fuzzy Multiple Criteria Decision Making Model (FMCDMM) to evaluate, identify and select an optimal robot system to perform the desired task from a large number of robot systems.

Koulouriotis and Ketipi (2014) presented an extensive, aggregated, and detailed review for Robot Selection Problem (RSP), including a wide variety of models, ranging from the first attempts which were developed in order to approach the issue to the most contemporary and flexible decision methodologies. In advance, these models were classified considering the pattern of RSPs and analyzed according to robots' attributes as well as to decision parameters. Rashid et al. (2014) proposed technique for order preference by similarity to ideal solution (TOPSIS) for selection of industrial robot in integration with trapezoidal fuzzy numbers set theory. The proposed method (F-TOPSIS) could aggregate the response of several Decision-Makers on different criteria, regarding a set of alternatives; where, the judgment of the Decision-Makers were represented by generalized Interval-Valued Trapezoidal Fuzzy Numbers (IVTFNs). The proposed methodology was validated with a case study.

Parameshwaran et al. (2015) incorporated a hybrid approach for the optimal selection of robots by taking both objective and subjective criteria into account. The methodology utilizes Fuzzy Delphi Method (FDM), Fuzzy Analytical Hierarchical Process (F-AHP), Fuzzy modified TOPSIS and Brown–Gibson model for robot selection. The developed approach was exemplified with a case study in order to select the best suitable robot for teaching purpose. Sahu et al. (2015a) provided a model using fuzzy logic and introduced some qualitative parameters to find out the best mobile robot alternatives. Authors utilized three different techniques viz. triangular, trapezoidal and Gaussian membership functions to determine the closeness of robot in accordance to the ability of robot. All the aforementioned techniques were compared; and amongst all, Gaussian membership function was found the most effective one for closeness measurement, as reported. Ghorabaee (2016) presented a multi-criteria group decision making approach i.e. Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method with interval type-2 fuzzy numbers set theory to handle the robot selection problem for a case auto company. The most suitable alternative (robot) was selected based on ideal and the nadir solutions as well, without defuzzification.

## 2.2 Supplier/ Vendor Selection

Suppliers are the dealers who provide raw materials, components and after sales service that an organization cannot self-give (Kuo et al., 2011). Hence, supplier selection becomes one of the important assignment in industrial context to attain the preferred level of quality and quantity at the reasonable cost with on-time delivery. Supplier selection is a common practice frequently performed by the organizations to identify, evaluate and contract with the suitable supplier in order to fulfill the demand. Dogan and Sahin (2003) used Activity-Based Costing (ABC) and fuzzy present worth techniques to perform supplier selection process for a Tekno-TV company (USA), operating on just-in-time environment. Kumar et al. (2004) applied a fuzzy goal programming approach for vendor selection. Authors presented a case study in an Indian manufacturing company dealing with auto parts to demonstrate effectiveness of the suggested model.

Amid et al. (2006) presented a fuzzy multi-objective linear model based on an asymmetric fuzzy decision making technique to encounter the ambiguity involved in the supplier selection process. The developed algorithm was demonstrated through a numerical example by considering cost, quality and service as a supplier selection criteria. Chen et al. (2006) developed a fuzzy based decision making technique to overcome supplier selection issues in supply chain system. In this paper, authors assigned the linguistic values to determine ratings and weights of the supplier selection criteria (viz. profitability of supplier, relationship closeness, technological capability, conflict resolution etc.). Finally, TOPSIS approach was used to find out the ranking order of the suppliers. Garfamy (2006) developed a Data Envelopment Analysis (DEA) model based on Total Cost of Ownership (TCO) concept to evaluate the performance of the suppliers. The proposed model was demonstrated for a hypothetical manufacturer by considering technical efficiency, after sales service, manufacturing cost, quality cost and technology cost as major criteria for supplier selection process. Perçin (2006) developed a framework by integrating Analytic Hierarchy Process (AHP) and Pre-emptive Goal Programming (PGP) approach for supplier selection problem. The developed model could easily tackle the qualitative as well as quantitative criteria (viz. flexibility, delivery reliability, technical capability, management skills, response to complaints, repair and maintenance service etc.) involved in supplier selection process. Further, the model was validated through a real-world application by utilizing the source data given by a manufacturing firm (in Turkey) functioning in an automotive industry.

Yang and Chen (2006) proposed Analytical Hierarchy Process (AHP) and Grey Relational Analysis (GRA) based decision making approach to serve the purpose of supplier selection for a notebook computer manufacturing company in China. Three suppliers were evaluated and ranked based on few qualitative (viz. quality, finance, customer service, technical capability etc.) and quantitative criteria (turnover, cost, distance etc.). Li et al. (2007b) developed an integrated decision making approach for supplier selection by using grey numbers set theory. Ratings and weights of criteria (viz. product quality, service quality, delivery time etc.) for all alternatives were represented in linguistic terms and assessed by through grey numbers. Finally, a grey possibility degree approach was used to rank the alternative suppliers.

Chou and Chang (2008) presented a fuzzy baed Simple Multi-Attribute Rating Technique (SMART) in a strategic management perspective to solve issues for solving the supplier/vendor selection. The proposed approach was studied empirically for a famous electronic company in Taiwan. Yang et al. (2008) developed an integrated fuzzy Multi-Criteria Decision Making (MCDM) technique for vendor selection problem. In the developed approached, triangular fuzzy numbers were used to assess the subjectivity involved in the vendor selection criteria information. Further, an Interpretive Structural Modeling (ISM) was used to explore the relationship between the various criteria and sub-criteria (quality, price, technology, responsiveness, lead time etc.). Next, the best choice was made based on the overall score of each vendor using the fuzzy weights with fuzzy synthetic utilities of the considered criteria. The model was applied into an electronic and Information Technology (IT) industries in Taiwan. Boran et al. (2009) developed a Multi-Criteria Decision Making (MCDM) method based on intuitionistic fuzzy numbers and TOPSIS approach for supplier selection issues. Intuitionistic Fuzzy Weighted Averaging (IFWA) operator was employed to aggregate the Decision-Makers' responses. Authors further demonstrated a case numerical illustration conducted for an automotive company at Turkey. Keskin et al. (2010) provided a fuzzy grounded Adaptive Resonance Theory (ART) algorithm for the selection of supplier in industrial context. The developed algorithm was applied to an automotive manufacturing company in Turkey; in which, based on the few criteria (viz. production capacity, technical capability of employee and equipment, managing diversification, financial capability, packing, transportation and logistics demands, work safety and labor health etc.) ten suppliers were evaluated and ranked. Kuo et al. (2010) suggested the integration of Particle Swarm Optimization (PSO) based Fuzzy Neural Network (FNN) and Artificial Neural Network (ANN) for supplier selection problem. The developed approach was implemented to select the PCB (Printed Circuit Board) supplier in a laptop/computer manufacturing company in Taiwan.

Amin et al. (2011) suggested the fuzzy SWOT (Strengths, Weaknesses, Opportunities and Threats) analysis and fuzzy linear programming based model to select the best candidate supplier. Authors applied the model to select the supplier for a auto parts supplying company in Iran. Dalalah et al. (2011) developed an integrated Multi-Criteria Decision Making approach through the application of DEMATEL (Decision Making Trial and Evaluation Laboratory) and TOPSIS in fuzzy environment for supplier selection. Authors further demonstrated application potential of the proposed model through case study for selection of supplier at Nutridar Factory in Jordan. Galankash et al. (2016) identified a Balance Scorecard (BSC) and fuzzy AHP (Analytical Hierarchy process) based integrated approach for supplier selection. The proposed model was employed to select the supplier in an automotive company at Malaysia.

The selection of suppliers may be carried out done according to their green, sustainable, resilient, agile and g-resilient capabilities. The efforts made by the past researchers towards selection of green, sustainable, resilient, and g-resilient suppliers have been discussed in **Section 2.2.1** to **Section 2.2.4**, of this chapter.

### 2.2.1 Green Supplier Selection

Green Supply Chain Management (GSCM) has become an important avenue in current business scenario. The concept of GSCM is to integrate environmental thinking into traditional supply chain management. More specifically, GSCM can contribute to a firm's sustainability performance enhancement. A firm's sustainability performance is greatly influenced by appropriate supplier selection in the green supply chain context. Appropriate supplier selection is one of the most decisive tasks of supply chain management because of its strategic importance. Selection and management of the right supplier are the only way to acquire the desired level of quality at the reasonable price with on time delivery. The present international business environment has forced many firms to focus on supply chain management to cope with highly increasing competition. Hence, supplier selection process has gained vital importance; since most of the firms are spending a considerable amount of their revenues on purchasing (Çebi and Bayraktar, 2003).

Continuous production may cause substantial hazards to the environment in terms of industrial pollution like emissions, discarded packaging materials, scrapped materials, and residuals. In order to save mother planet the ‘Earth’ from all these threat, green supply chain management has been evolved and considered as an environmental innovation. GSCM intends to eliminate wastages including hazardous chemical, emissions, energy and solid waste along supply chain network activities such as product design, material resourcing and selection, manufacturing process, delivery of final product and end-of-life management of the product (Chin et al., 2015; Rao, 2006; Srivastava, 2007). GSCM has its roots in both environmental management and supply chain management literature. Adding the ‘green’ component to supply chain management involves addressing the influence and the relationships between supply chain management and the natural environment (Srivastava, 2007).

All supply chain activities must be synchronized by incorporating green practices. Moreover, green practices in supply chain management can support organizations to improve their end-to-end operations which may result in greater cost savings and profitability. Strict government rules and public awareness have forced many organization s to ‘go for green’ policies in order to save the environment and the atmosphere. Due to rapid technological developments and industrialization, control on carbon footprint, pollution, air emission etc. have become indeed a necessity. Progressively, purchasing managers are being forced not only to reconstruct the relationship with the suppliers into a more tactical way but also to incorporate environmental thinking on their decisions. Traditionally, organizations used to consider factors like quality, flexibility, etc. when evaluating the supplier’s performance. Since, environmental pressure is increasing; green image of supplier’s is established as an emerging issue between the manufacturing firms; as green suppliers may contribute towards the environmental pollution control. In selecting appropriate green supplier, various green criteria (like pollution control, environmental management, green product, green competencies etc.) are to be consider along with traditional supplier selection criteria (viz. cost, delivery, performance etc.). Past researchers have identified numerous green criteria and performed supplier selection process with the help of different MCDM methods.

Handfield et al. (2002) applied Analytical Hierarchy Process (AHP) as a decision making tool to help managers regarding trade-offs understanding between environmental dimensions. Three case studies in the different manufacturing units viz. automobile, paper and apparel were exemplified to determine the benefits and weaknesses of applying AHP. Humphreys et al. (2003) developed a framework by integrating environmental factors into the supplier selection process. The recognized criteria were separated into two main categories: quantitative environmental criteria (viz. chemical waste, water waste, energy etc.) and qualitative environmental criteria (viz. recycle, reuse, disposal, re-manufacture, ISO 14001 certification, clean technology available etc.). Further a knowledge based system was used to illustrate the supplier selection problem. Lu et al. (2007) presented a multi-objective decision support system for green supply chain management in order to help the supply chain manager in measuring and evaluating suppliers' performance based on AHP. In order to reduce subjective bias in designing a weighting system, a fuzzy logic process was used to modify the AHP.

Lee et al. (2009) proposed a model for evaluating green suppliers for high-tech industry. The Delphi method was applied first to differentiate the criteria for evaluating traditional suppliers and green suppliers. A hierarchy was constructed next to evaluate the importance of the selected criteria and the performance of green suppliers. In order to consider vagueness of experts' opinion, the fuzzy extended analytical hierarchy process was utilized. Jabbour and Jabbour (2009) verified if Brazilian companies were adopting environmental requirements in their supplier selection process. Further, this paper analyzed the relation between the level of environmental management maturity and the inclusion of environmental criteria during supplier selection. Awasthi et al. (2010) presented a fuzzy multi-criteria decision making approach to evaluate the environmental performance of suppliers. The suggested approach was applied in three different steps viz. criteria identification, expert rating (linguistic) and linguistic assessment for criteria and alternatives. The linguistic ratings were combined through fuzzy TOPSIS approach to achieve an overall performance score for each alternative. The environmental performance of the supplier was supposed to be high possessing maximum overall score.

Ma and Liu (2011) provided an evaluation index system associated with DEA/AHP comprehensive analysis for supplier selection based on the green supply chain. Shaik and Abdul-Kader (2011) presented a generic framework integrating environmental and social criteria leading to a comprehensive selection process of green suppliers. This study proposed a framework consisting of environmental (E), green (G) and organizational (O) factors required for the green supplier selection process. In order to cater to the multi-criteria decision making approach with both quantitative and qualitative attributes; the authors applied the multiple attribute utility theory that could help the managers formulating viable sourcing strategies. Wu et al. (2011) explored the fuzzy DEMATEL (Decision Making Trial and Evaluation Laboratory) method to find influential factors in selecting GSCM criteria. The DEMATEL method evaluated supplier's performance to find key factor criteria to improve performance and provided a novel approach of decision making information in GSCM implementation.

Shaw et al. (2012) presented an integrated approach for selecting the appropriate supplier in the supply chain, addressing the carbon emission issue, using fuzzy-AHP and fuzzy multi-objective linear programming approaches. Fuzzy-AHP was applied first for analyzing the weights of the multiple factors. The considered factors were cost, quality rejection percentage, late delivery percentage, greenhouse gas emission and demand. These weights were used in fuzzy multi-objective linear programming for supplier selection and quota allocation. Büyüközkan and Çifçi (2012b) examined GSCM capability dimensions and thereby proposed an evaluation framework for green suppliers. The identified components were integrated into a hybrid fuzzy multi-criteria decision making model combined with the fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL) model, the Analytical Network Process (ANP), and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), in a fuzzy context. A case study was proposed for green supplier evaluation in a specific company, named Ford Otosan in Turkey. Büyüközkan (2012) proposed a decision model for supplier performance evaluation by considering various environmental performance criteria. A fuzzy analytic hierarchy process was applied to determine the relative weights of the evaluation criteria and an Axiomatic Design (AD) based fuzzy group decision making approach was applied to rank the candidate green suppliers.

Büyüközkan and Çifçi (2012b) examined the components and elements of GSCM and suggested a GSCM evaluation framework. The work also provided a real case study of Ford Otosan in Turkey. The identified components were integrated into a strategic assessment and evaluation tool using Analytical Network Process (ANP). Moreover, to cope up with ambiguity and vagueness of the Decision-Maker's evaluations, the fuzzy extension of the ANP method was referred in this research. Sahu et al. (2012)

developed a measurement index evaluation system towards assessing suppliers' green performance practices. A grey based supplier appraisement platform was established in this work. Application of Grey-Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and COPRAS-G method were exploited to solve the said supplier selection problem. Kannan et al. (2013) presented an integrated approach by considering fuzzy multi-attribute utility theory and multi-objective programming for rating and selecting the best green supplier according to economic and environmental criteria.

Dehghani et al. (2013) proposed an approach by employing fuzzy-ANP for supplier selection and allocations taking into account the environmental implications. In order to verify applicability of the proposed approach, purchasing process of Asia Pishro Diesel Company, Iran was reviewed as a case study. Bali et al. (2013) presented an integrated MCDM method based on Intuitionistic Fuzzy Set (IFS) and Grey Relational Analysis (GRA) for green supplier selection. The proposed approach was studied empirically for an automobile company in order to perform the green supplier selection process in uncertain environments. Shen et al. (2013) proposed a fuzzy multi-criteria methodology for the assessment of green suppliers. Fuzzy set theory was applied to interpret the subjective human perceptions (linguistic preferences) into equivalent crisp score. Linguistic preferences were assessed through fuzzy-TOPSIS to generate an overall performance score for supplier's evaluation.

Dobos and Vörösmarty (2014) examined the extension of the vendor evaluation methods with environmental, green issues. In this method, the authors divided the criteria in two categories: the traditional (managerial) and environmental (green) factors. Subsequently, with the help of Composite Indicators (CI), a weight system was determined with which the environmental criteria could influence the decision with a representation of the green factors. In this study, a weight system was presented to determine the environmental factors, as an important decision factors. In order to choose the particular weight system, the authors applied Data Envelopment Analysis (DEA) with the Common Weights Analysis (CWA) method. Blome et al. (2014) adopted the opposing theoretical views of legitimacy institutional and strategic in evaluating firm's performance and top management commitment as antecedents to green procurement and green supplier development. Additionally, the impact of green procurement and green supplier development on supplier performance was analyzed.

The paper addressed a research gap concerning firm-level antecedents for green procurement and green supplier development showing that both practices might impact supplier performance.

Bakeshlou et al. (2014) developed a multi-objective fuzzy linear programming framework by integrating fuzzy-DEMATEL to the ANP approach for a Green Supplier Selection (GSS) problem. Hybrid of fuzzy ANP and fuzzy multi-objective linear programming were illustrated to allocate the optimal ranking order of the considered suppliers. Kannan et al. (2014) suggested a decision support framework using F-TOPSIS to identify and select green suppliers. Input data were collected from various supplier sources. Rank obtained by fuzzy-TOPSIS was compared with geometric mean and the graded mean approaches of fuzzy-TOPSIS. Spearman rank correlation coefficient was finally utilized to explore the statistical difference amongst the ranks obtained by aforesaid three different approaches. The study was carried out empirically for an electronics company in Brazil. Ashlaghi (2014) proposed a hybrid approach for green supplier selection. The proposed approach consisted of three phases. First, the Fuzzy Decision Making Trial and Evaluation Laboratory (FDEMATEL) method was applied to construct interrelations among the criteria determined for evaluating green suppliers. Then, the criteria weights were determined through Fuzzy Analytical Network Process (FANP). Lastly, a linear physical programming model was applied in order to obtain the best suppliers.

Dou et al. (2014) introduced a grey Analytical Network Process (grey ANP) based model to identify green supplier development programs in order to improve suppliers' performance. The authors further evaluated green supplier development programs with explicit consideration of suppliers' involvement propensity levels. Hashemi et al. (2015) proposed a comprehensive green supplier selection model by using both economic and environmental criteria. The authors utilized ANP and an improved grey relational analysis approach to weight the criteria and to rank the suppliers, respectively. Galankashi et al. (2015) provided an integrated procedure to consider both classical and green key performance indicators within the supplier selection framework. Nominal Group Technique (NGT) was deployed to extract the most critical performance measures. A Fuzzy Analytical Network Process (FANP) was deployed to weight the extracted measures and to determine their importance level.

Fallahpour et al. (2015) recommended an integrated assessment framework for green supplier selection in the context of fuzzy environment with application of Data Envelopment Analysis (DEA) and genetic programming approach. Hu et al. (2015) investigated the optimization decision problem of supplier selection in green procurement under the mode of low carbon economy. Freeman and Chen (2015) focused on development of a green supplier selection model using an index system based on a combination of traditional supplier and environmental supplier selection criteria. The authors adopted AHP-Entropy-TOPSIS framework to facilitate the said decision making problem. Ghayebloo et al. (2015) developed a bi-objective mixed integer programming model and solved for a forward/reverse logistic network including three echelons in the forward direction (suppliers, assembly centers and customer zones) and two echelons in the reverse direction (disassembly and recycling center). A set of Pareto optimal solutions was obtained to show the trade-off between the profit and the greenness objectives. Kuo et al. (2015) proposed a hybrid MCDM method to evaluate green suppliers in an electronics company. A set of criteria in two dimensions concerning environmental and management systems were identified under the Code of Conduct of the Electronic Industry Citizenship Coalition (EICC). Following this, the Decision Making Trial and Evaluation Laboratory (DEMATEL) used the Analytic Network Process (ANP) method (known as DANP) to determine both the importance of evaluation criteria in selecting suppliers and the causal relationships between them. Finally, the VIKOR method was used to evaluate the environmental performance of green suppliers.

Banaeian et al. (2015) proposed an operational model including general and environmental criteria for green supplier selection. Analytic Hierarchy Process (AHP) and Delphi method was used to determine the weight of considered criteria. Finally, Fuzzy Grey Relational Analysis (F-GRA) Method was applied to rank the suppliers. Author further validated the proposed approach by conducting a case study for a food industry (in European Union). Banaeian et al. (2016) applied TOPSIS, VIKOR and GRA methods in fuzzy environment and provided a hybrid decision making framework for green supplier selection. The green performance of candidate supplier alternatives were evaluated through exploration of the three different methodologies viz. F-TOPSIS, F-VIKOR, F-GRA. The proposed model was applied to the agro-food industry Iran, for the possible selection of green supplier.

Yu and Hou (2016) presented a Modified Multiplicative Analytic Hierarchy Process (MMAHP) method for solving green supplier selection problem. Authors further carried out a case study by applying their model to select the green suppliers by considering some environmental criteria (viz. green degree level, resources recycling ability, energy utilization ability etc.) for an automobile manufacturing firm situated at Qingdao, China.

Literature depicts that supplier selection in green supply chain management is being viewed as a critical success factor for the modern business today. It is clearly understood that supplier selection should be carried out in view of suppliers' 'green' criteria along with traditional criteria (viz. cost, quality, delivery performance, reliability etc.). A firm's sustainability also depends on effective supplier selection by considering economic criteria, green criteria as well as social criteria [Bai and Sarkis, 2010a; Büyüközkan and Çifçi, 2011; Amindoust et al., 2012; Azadnia et al., 2012; Dai and Blackhurst, 2012; Orji and Wei, 2014; Chaharsooghi and Ashrafi, 2014; Azadnia et al., 2015; Linton et al., 2007; Walker et al., 2008; Chu et al., 2009; Carter and Rogers, 2008].

### 2.2.2 Sustainable Supplier Selection

The purpose of sustainable Supply Chain Management (SSCM) is to integrate economic and social thinking along with environmental awareness into the traditional supply chain management. The sustainability in supply chain comes into existence right from the product design and development to the material selection, manufacturing, packaging, transportation, warehousing, distribution, consumption, return, and disposal (Linton et al. 2007; Walker et al., 2008; Chu et al., 2009; Büyüközkan and Çifçi, 2011).

In supply chain management, supplier selection has long been viewed as a Multi-Criteria Decision Making (MCDM) Problem. In traditional supplier selection, the criteria like cost, quality, delivery requirement and service etc. are generally considered. Today's market demand has enforced supply chain managers towards emphasizing sustainability concepts to be embedded into the supply chain management. Supply chain that is driven by the 'green' concepts is known as Green Supply Chain (GSC). Greening the supply chain is one of the components to ensure a firm's sustainability. A sustainable supply chain must adhere to the green principles along with business (economic) as well as social criteria. In view of sustainability issues, potential suppliers must be selected by considering economic sustainability, environmental (green) sustainability as well as social sustainability criteria.

Bai and Sarkis, (2010a) and Dou and Sarkis, (2010) took an initial step to consider sustainability as the criteria for supplier selection process; afterwards, (Dai and Blackhurst, 2012) reported that the method developed by (Bai and Sarkis, 2010a) and (Dou and Sarkis, 2010) did not capture the ‘voice’ of the stakeholders; the authors focused on the ‘voice’ of the customer; as, according to (Porter, 1990) customers have a profound influence on companies with regard to product performance, product safety, and environmental impact.

In order to achieve a sustainable supply chain, all the chain members from the suppliers to the top managers must have an affinity with sustainability (Amindoust et al., 2012). Sustainable development and sustainability are frequently interpreted as a synthesis of economic, environmental and social development well known as a triple-bottom-line approach (Gauthier, 2005).

Sustainability has been viewed as a major concern for organizations as awareness about environmental degradation, natural resource depletion, and climate change have increased considerably. In addition, voices raised by social organizations on various social and environmental issues in developing countries have forced organizations to focus on sustainable manufacturing practices (Mani et al., 2014). Hence, the study of sustainable supply chain management has gained immense momentum during past two decades. Although the studies focused on three pillars of sustainability viz. economic (profit), environment (planet) and social (people); the social aspect was not explored much due to the ‘humanness’ and the difficulty in getting tangible outcomes from it (Elkington, 1998; Carter and Easton, 2011; Ashby et al.2012).

Recently, industries have come to know that the evaluation of suppliers must be done on the basis of sustainability perspective and hence a triple-bottom-line (economic, social, and environmental performance) approach into supplier assessment and selection decisions has been introduced to implants a new set of trade-offs (Dai and Blackhurst, 2012). Because of the fast and agile developments in the technology, purchase department has become the fully responsible authority to play this crucial role of selection of potential supplier in all respect. Bai and Sarkis (2010a) integrated sustainability issues into supplier selection problem using grey system and rough set methodologies. Verdecho et al. (2010) proposed an approach to select suppliers for sustainable collaborative networks using a performance management framework. Büyüközkan and Çifçi (2011) delivered a model based on sustainability principles for supplier selection operations in supply chains. The developed model was integrated with fuzzy analytic network process within multi-person decision making schema under incomplete preference relations. Goebel et al. (2012) explored the concept based on ethical culture, and identified elements for guiding Purchasing and Supply Management (PSM) behavior towards socially and environmentally sustainable supplier selection. Results indicated that different elements of the firms' ethical culture had a significant impact on how purchasing managers would account for social and environmental criteria when selecting potential suppliers. Amindoust et al. (2012) determined sustainable supplier selection criteria as well as sub-criteria and proposed a methodology for evaluation and ranking of a given set of suppliers. In order to handle the subjectivity of Decision-Makers' assessments, fuzzy logic was applied and a ranking method on the basis of Fuzzy Inference System (FIS) was proposed for supplier selection problem.

Azadnia et al. (2012) proposed an integrated approach of clustering and multi-criteria decision making methods to solve sustainable supplier selection problem. Firstly, self-organizing map was utilized in order to cluster and prequalify the suppliers based on customer demand attribute and sustainability elements. Then, multi-criteria decision making methods were utilized to rank the cluster of suppliers, to make coordination between them and customers. Dai and Blackhurst (2012) developed an integrated analytical approach, combining Analytical Hierarchy Process (AHP) with Quality Function Deployment (QFD), to enable the 'voice' of company stakeholders in the process of supplier assessment from a sustainability perspective. Drawing on the sustainable purchasing strategy development process, the proposed AHP–QFD approach comprised four hierarchical phases: linking customer requirements with company's sustainability strategy, determining the sustainable purchasing competitive priority, developing sustainable supplier assessment criteria, and lastly assessing the suppliers.

Gimenez and Tachizawa (2012) revealed that both assessment and collaboration had a positive impact on environmental performance and corporate social responsibility. The paper summarized knowledge related to the impact of supplier assessment and collaboration on sustainability, and described the enablers of such initiatives.

Molamohamadi et al. (2013) presented a structure which considered all of the influential relations between the members of the supply chain. Based on the proposed framework, the essential supplier selection measures and criteria were discussed. As a result, the offered scheme could be used by the manufacturers to select the most appropriate suppliers contributing to the movement of the supply chain towards sustainability. Ghadimi and Heavey (2014) examined on sustainability evaluation of suppliers, specifically operating in medical device industry using a Fuzzy Inference System (FIS).

Chaharsooghi and Ashrafi (2014) explored sustainability in supply chain management and examined the problem of identifying a model for supplier selection based on extended model of TBL (Triple Bottom Line) approach in supply chain by presenting fuzzy multi-criteria method. Linguistic values of experts' subjective preferences were expressed with fuzzy numbers and Neo-fuzzy-TOPSIS was proposed for finding the best solution to the supplier selection problem. Orji and Wei (2014) developed a model based on integrated MCDM methods to solve sustainable supplier selection problems. The model applied Fuzzy logic, DEMATEL and TOPSIS to effectively analyze the interdependencies between sustainability criteria and to select the best sustainable supplier in fuzzy environment while capturing all subjective and objective criteria. Mani et al. (2014) focused on socially sustainable supplier selection through social parameters by using the AHP process in decision making. This methodology demonstrated the development of social sustainability indicators, including equity, health, safety, wages, education, philanthropy, child and bonded labor. Jauhar et al. (2014) presented an approach to find a solution to the sustainable supplier selection problem using Differential Evolution in pulp and paper industry. This paper presented an approach to select efficient sustainable suppliers providing the maximum fulfillment for the sustainable criteria determined.

Sarkis and Dhavale (2015) developed a methodological approach based on a Bayesian framework and Monte Carlo Markov Chain (MCMC) simulation to rank and select suppliers using specific selection objectives. In evaluating and selecting sustainable suppliers, the authors took a triple-bottom-line (profit, people and planet) approach and considered business operations as well as environmental impacts and social responsibilities of the suppliers. Gold and Awasthi (2015) proposed a two-step fuzzy-AHP methodology for sustainable global supplier selection in an uncertain environment. The suggested framework could be used to deal with the problem of global sustainable supplier selection. Azadnia et al. (2015) proposed an integrated approach of rule-based weighted fuzzy method, fuzzy analytical hierarchy process and multi-objective mathematical programming for sustainable supplier selection and order allocation combined with multi-period multi-product lot-sizing problem. Neumüller et al. (2015) presented a problem specific comprehensive methodology for the optimal selection of suppliers in the context of sustainability issues. A hybrid model combining ANP and Goal Programming (GP) was developed for the selection of hybrid car supplier and validated through a case example for an automotive industry in Germany.

Orji and Wei (2015) presented a modeling approach of integrating information on supplier behavior in fuzzy environment with system dynamics simulation modeling technique. Supplier behavior with respect to relevant sustainability criteria in the past, current and future time horizons were sourced through expert interviews to select the best possible sustainable supplier. Simulation results showed that an increase in the rate of investment in sustainability by different suppliers caused an exponential increase in total sustainability performance of the suppliers.

### 2.2.3 Resilient Supplier Selection

Zhu et al. (2008) stated that the green paradigm is concerned with environmental risks and environmental impact reduction only and does not consider the effects of disturbances on the system. To handle such system disturbances (Christopher and Peck, 2004) developed a resilient supply chain concept and stated that the resilient paradigm focuses on the supply chain ability to recover to the desired state after a disruption occurs. Resiliency is an adaptive control term where organizations prepare themselves to cope up with any unfortunate/unexpected event or demand by ensuring the continuity of the operation at the best possible way. It is also defined as the capacity of a system to attain its original state after disruption takes place. According to (Fiksel, 2006), resiliency refers to a firm's capacity to survive, adapt and grow in the face of change and uncertainty. A rare attempt is made to address the resilient supplier selection problem.

Haldar et al. (2012) established a quantitative approach for supplier selection under a disaster environment. Supplier's weights were initially determined using TOPSIS and AHP methodology for general selection criteria. Using AHP-QFD methodology, the manufacturer's critical criteria and resiliency criteria were integrated into the selection process; to determine the Subjective Factor Measures (SFM) for each of the primarily selected suppliers. Different cost factors were unified using a normalizing technique to determine the Objective Factor Measure (OFM) for each of the candidate suppliers. Finally, a supplier selection index was calculated in which the Decision-Maker's attitude played an important role.

In another reporting (Haldar et al., 2014) provided an approach for strategic supplier selection, under a fuzzy environment, in a disaster scenario. This paper presented an integrated fuzzy group decision making approach based on a fuzzy technique for TOPSIS to rank the suppliers in relation to a manufacturing system. Suppliers' weights for a general strategy and a resilient strategy were combined in course of sensitivity analysis; where, Decision-Makers' risk bearing attitude played an important role. Using this approach, organizations could devise resiliency plans to alleviate the vulnerability of a supply chain system. Pramanik et al. (2016) developed a quantitative approach that could handle the conflicts between different Decision-Makers and measured the performance of the suppliers in a manufacturing system to select a resilient supplier. In the proposed methodology, distance based optimization methodology, i.e. TOPSIS (Technique for Order Preference by Similarity to the Ideal Solution) integrated with fuzzy system, identified the features of general selection criteria. Finally, a supplier selection index was calculated in which the Decision-Maker's attitude was considered in providing a rational decision.

### 2.2.4 G-Resilient Supplier Selection

In order to make the supply chain environment friendly, the philosophy of green paradigm (i.e. green supply chain; GSC) has been introduced. Additionally, to cope up with the effects of disturbances/disruption situation within the system; the concept of resilient supply chain (RSC) has been introduced. 'Resiliency' in supply chain is the ability to recover to the desired (stable) state after a disruption occurs. Natarajarathinam et al. (2009) emphasized the need on developing scales for estimating supply chain resilience.

Mollenkopf et al. (2010) also stated that indeed there is a lack of integrated metrics and measurement methods that can cover green strategies throughout the supply chain. In industrial context, the resiliency is an adaptive control term; where, managers maintain a system for the recovery of the organization after any unexpected event or demand by promising the continuity of the operation at the best possible rate. Thus, supply chain resilience is supposed to be a highly desirable network, as it escalates a firm's readiness in dealing with risks that can appear from the customers' side or from the suppliers' side (Purvis et al., 2016). Azevedo et al. (2013a) proposed a decision making framework based on ISM approach to identify and rank a set of supply chain performance measures (criteria) for an automotive case company based on a criteria set combining green as well as resiliency capabilities of the supply chain.

## 2.3 Third Party Logistics (3PL) Service Provider Selection

A third-party logistics (3PL) is a logistics service provider, normally asset-based, that emphases on specific elements of the supply chain in order to optimize the physical movement of goods from the point-of-origin to the end-user (Stock and Lambert, 2001) and, return of defective products from customer to the corresponding supplier (Meade and Sarkis, 2002). Generally, a company offering amenities or products is acknowledged as the first party; the customer(s) as the second party. A third-party, next, is an organization hired to perform such functions which neither the first nor the second party is ambitious to perform. A 3PL firm is a firm that offers outsourced or 'third party' logistics services to the industries for some portion or all of their supply chain management functions (Green et al., 2008).

To provide the warehousing and transportation related services for the industries/organization/supplier, so that the desired product can reach up to the user from supplier (or from user to supplier: i.e. 3PL reverse logistic service) is the absolute focus of the 3PL service provider body/firm. As 3PL service providers are solely responsible for the execution of the logistic related services of a company, the selection of 3PL service provider has got a vital importance in past few decades. While going through the selection process of 3PL service provider, supply chain managers may encounter numerous issues like, how to recognized the criteria for the selection of 3PL service provider; how to normalize and weight (i.e. importance of criteria) the criteria; how to explore the structural relationship between criteria, how to utilize the knowledge of experts and Decision-Makers (DMs) and so in.

3PL service provider selection process is difficult to perform, as it needs the assessment of plenty of criteria (subjective and objective; beneficial and cost) during the entire selection process. Analysis of such criteria and thereof, to measure the logistic performance of the 3PL service providers has been the key focus of past researchers (Efendigil et al., 2007). So et al. (2006) applied AHP to examine the service quality of 3PL service providers. Initially, the authors conceptualized few dimensions for selection criteria for 3PL service providers (viz. reliability, responsiveness, assurance and empathy etc.); and then used AHP approach to find out the relative weights of the aforementioned dimensions to select the best 3PL service provider eventually. Bottani and Rizzi (2006) presented a multi-attribute approach combining TOPSIS technique and the fuzzy set theory for the selection and ranking of the most suitable 3PL service provider. Karagul and Albayrakoglu (2007) suggested an AHP based MCDM framework for selection of the best 3PL service provider in order to execute the outsourcing/logistics services in the Turkish automotive industry. Qureshi et al. (2007) proposed a framework for 3PL service provider selection based on AHP. The weights of criteria were determined by the application of AHP approach while TOPSIS was used next to serve the purpose of selecting the best 3PL service provider. Kannan (2009) proposed a structured model by adopting multi-criteria decision making tools such as AHP and fuzzy Analytic Hierarchy Process (F-AHP) for evaluating and selecting the best third party reverse logistic (3PRL) service provider under fuzzy environment for the battery industry.

Perçin (2009) provided a MCDM model in combination with AHP and TOPSIS approach to evaluate the performance of 3PL service providers. Qureshi et al. (2009a) proposed a hybrid methodology for selection of 3PL service provider based on AHP and Graph Theory. A Logistics Service Provider (LSP) selection index was developed to rank various 3PL provider alternatives. The authors also suggested coefficients of similarity, coefficients of dissimilarity followed by an identification sets to compare the performance of alternative 3PL service provider candidates. Qureshi et al. (2008a) presented a model based on the Interpretive Structural Modeling (ISM) to identify and to classify the key selection criteria of 3PL services providers. The key criteria (viz. quality of service, delivery performance, IT capability, financial stability, long term relationship, reputation, optimum cost, surge capacity, geographical spread and range etc.) considered in this paper were modeled through ISM approach to find out their interrelationship and mutual influence on the entire selection process. Driving and dependence power of various key criteria were calculated and based on that criteria were placed under four broad classifications viz. dependent, independent, autonomous and linkage. Liu and Wang (2009) presented an integrated fuzzy approach for evaluation and selection of 3PL service providers. The method consisted three different techniques: (1) fuzzy Delphi method to identify important evaluation criteria; (2) fuzzy inference method to eliminate unsuitable 3PL service providers; and, (3) fuzzy linear assignment approach for the final selection.

Gupta et al. (2010) recommended a 3PL service provider selection framework through the application of fuzzy-Delphi method in integration with TOPSIS approach. Further authors used fuzzy-TOPSIS approach to choose the best 3PL service provider. Chen and Wu (2011) proposed a hybrid decision making framework by integrating the Delphi method and ANP approach. The authors further validated the developed model through a case study in an electronic company located in South Asia. Govindan and Murugesan (2011) proposed a structured model using fuzzy extent analysis to select a 3PRL service provider under fuzzy environment for an Indian battery industry. Gupta et al. (2012) developed a model to select the best 3PL service provider alternative in a MCDM environment. Fuzzy-PROMETHEE technique was applied using Decision Lab 2000 software. A case study was performed for a cement company to select the logistic service providers to demonstrate the ease and effectiveness of the proposed model.

Li et al. (2012) developed a 3PL supplier selection model based on fuzzy sets. Authors further, established a comprehensive evaluation framework through a compound quantification based procedure for 3PL supplier's selection on fuzzy environment. Finally, a real-world case analysis was provided to validate the suggested model for an air conditioner manufacturing company in China. Peng (2012) conducted a research on the evaluation and the selection of 3PL service provider using AHP approach. This study provided a reference for an enterprise to choose logistics outsourcing service suppliers. Wong (2012) developed a decision support system for 3PL provider selection in global supply chain using multi-objective optimization model along with the opinion of the experts. The proposed model was based on the F-ANP and PFIGP (Preemptive Fuzzy Integer Goal Programming) approaches. Min et al. (2013) evaluated the managerial capability of few leading 3PLs in North America and recognized the best practiced firms amongst the considered 3PLs. The authors proposed DEA approach to measure the slack-based efficiency, technical efficiency, and mixed efficiency of considered leading 3PLs.

Akman and Baynal (2014) developed an integrated fuzzy multi-criteria decision making approach for logistics service provider selection. The proposed model consisted two different techniques: (1) F-AHP to determine the criteria weight (2) F-TOPSIS to evaluate and to rank the alternatives for final decision making. An industrial application of the developed model was carried out in logistics department of a tire manufacturing company in Turkey. Prakash and Barua (2016) proposed an integrated model under fuzzy environment for 3PRLP selection. The author further proposed F-AHP and F-TOPSIS to identify the suitable 3PRLP for an Indian electronics company.

## 2.4 Supply Chain Performance Assessment

The supply chain has been traditionally defined as a one-way, integrated manufacturing process wherein raw materials are converted into final products, then delivered to the customers (Beamon, 1999). Under this explanation, the supply chain comprises only those happenings related with manufacturing from raw material procurement to final product delivery. Management of an organization's supply chains has been established as an effective mechanism in order to provide prompt delivery of products and services at the least cost. To attain this, performance evaluation of the entire supply chain appears indeed important. Due to, increased complexity in supply chain network, past researchers suggested the need for evaluation and monitoring the performance, particularly in those circumstances where supply chains are considered a key factor of corporate achievement (Bigliardi and Bottani, 2014).

Performance measurement plays a significant role in managing a business or commercial activities, as it provides the necessary information that is useful for further developments and eventually to provide an effective decision making along with further course of actions (Gunasekaran and Kobu, 2007). As per (Kaplan, 1990) 'No measures, no improvement'. Hence, it is essential to evaluate the right things at the right time in supply chain so that timely action can be taken. Apart from that, many organizations/firms are not receiving the value as they expected from their supply chain. In this sense, the assessment of supply chain performance becomes mandatory and need of the hour, as measuring the performance would be decisive towards the development of supply chains. Recently, supply chain performance assessment have acknowledged with much attention from various researchers. Supply chain performance refers to the extended supply chain's activities in operation like end-customer requirements, ensuring product availability, on-time delivery in a responsive manner. Supply chain performance assessment can be categorized broadly into two levels viz. qualitative assessment (such as customer satisfaction and product quality) and quantitative assessment (such as order-to-delivery lead time, supply chain response time, resource utilization etc.). Performance assessment have an important role to play in setting objectives, evaluating performance, and determining future courses of actions for the organizations (Gunasekaran et al., 2004).

Enhancing the supply chain performance needs a multi-dimensional policy that addresses how organization will tackle diverse customer requirements. The literature on supply chain performance evaluation deals with pro-active strategies for successfully managing a supply chain is fairly enormous. Thakkar et al. (2009) presented an integrated supply chain performance measurement model for Small and Medium Scale Enterprises (SMEs). In this article the supply chain performance measurement framework was developed by using the Balanced Scorecard (BSC) and Supply Chain Operation Reference (SCOR) model. Hofmann and Locker (2009) developed a value-based performance measurement concept in supply chains on the basis of a case study from a packaging industry. Kim (2010) suggested a framework for evaluating the comprehensive performance of Supply Chain Partnership (SCP). The developed framework was based on the self-assessment dimensions and tactics of the business excellence model developed by the European Foundation for Quality Management (EFQM).

Shafiee and Shams-e-alam (2011) proposed a method based on Rough Data Envelopment Analysis (RDEA) for evaluating the performance of supply chain. Khilwani et al. (2011) developed an effective modeling technique named ‘hybrid Petri-net’, to control the dynamic behavior of the supply chain effectively. The developed model was subsequently used for risk management to examine the issues of supply chain vulnerability and risk. Banomyong and Supatn (2011a) presented a supply chain performance assessment methodology that could assess the performance of key supply chain activities of a company under numerous performance dimensions (viz. cost, time, reliability etc.). Ip et al. (2011) suggested an integrated framework to measure the supply chain performance and stability using System Dynamics (SD). A case study was performed at a typical semiconductor equipment manufacturing company in Hong Kong to demonstrate and to validate the proposed model. Effectiveness and efficiency, with few indicators (such as: product reliability, employee fulfillment, customer fulfillment, on-time delivery etc.) were found to be the most important factors in the performance of the supply chain.

Saadany et al. (2011) developed an analytical decision model to examine the performance of a supply chain network wherein, product, process, environmental quality etc. were considered as a supply chain characteristics in this paper. Bai and Sarkis (2012) introduced a neighborhood rough set approach using elements of the Supply Chain Operations Reference (SCOR) model.

Najmi and Makui (2012) presented a conceptual decision making model model for measuring supply chain performance using AHP and DEMAT methods. Estampe et al. (2013) analyzed various models like Activity-Based Costing (ABC), Framework for Logistics Research (FLR), Balanced Score Card (BSC), Supply Chain Operation Reference model (SCOR), Strategic Audit Supply Chain (SASC), World Class Logistics model (WCL), Efficient Customer Response (ECR), Supply Chain Advisor Level Evaluation (SCALE), Strategic Profit Model (SPM) etc. to assess the performance of supply chain system. Chen and Gong (2013) suggested a methodology for assessing the performance of a supply chain network. In this paper, the cost factors (viz. production costs, disruption costs, coordination costs, and vulnerability costs.) were considered.

Vaidya and Hudnurkar (2013) proposed a decision making approach based on AHP to assess the performance of supply chain in an Indian case chemical company. Aramyan et al. (2007) suggested a MCDM model to measure the supply chain performance in an agri-food supply chain (Germany). Four main categories of performance assessment viz. efficiency, flexibility, responsiveness, and food quality were recognized as chief performance components of the supply chain performance measurement system. Kamalabadi et al. (2008) presented an approach to supply chain performance measurement by the exploration of FMADM (Fuzzy Multi-Attribute Decision Making) method. Xu et al. (2009) conducted a study to measure the supply chain performance of a furniture manufacture industry in China by using using Rough Data Envelopment Aanalysis (RDEA). Elgazzar et al. (2012) developed a supply chain performance measurement framework by using Dempster Shafer/Analytical Hierarchy Processes (DS/AHP) approach. Authors further, proposed a Supply Chain Financial Link Index (SCFLI) to examine supply chain performance indicators contributing more towards the company's financial strategic objectives. Apart from the traditional supply chain performance assessment, many authors have developed frameworks to measure the performance of green, resilient and g-resilient supply chains (as discussed in **Section 2.4.1** to **Section 2.4.4)**

### 2.4.1 Performance Evaluation of Traditional Supply Chain

Traditional supply chain management is cost and quality oriented. In such kind of supply chains organizations have modest ability to respond to changes. The frequently used term for the evaluation of traditional supply chains' performance are quality, delivery, flexibility, cost, and response (Ketchen and Hu, 2007). Towards the evaluation of traditional supply chain performance, attempt of distinguished pioneers have been discussed. Felix and Qi (2003) proposed a performance measurement method in order to contribute towards the improvement of supply chain management. A process-based systematic perspective was developed and utilized to make a model that could measure the holistic performance of complex supply chains. To address the real situation in judgment and evaluation processes Fuzzy Set Theory (FST) was used as a key tool.

Yang (2009) proposed a performance evaluation index system to examine the efficiency and benefits of supply chain. An enhanced Balanced Scorecards (BSC) was developed therein. In this paper, fuzzy logic was recognized as an effective way to determine the uncertainty and ambiguity in evaluating supply chain performance. El-Baz (2011) presented a performance measurement approach based on fuzzy theory and the pair-wise comparison of AHP. In the anticipated model, various input factors (viz. new product design, distributed cost, customer response, on-time delivery, efficiency, product quality etc.) were assessed. Olugu and Wong (2012) explored an expert fuzzy rule-based system using Visual Basic.Net for performance evaluation of a closed-loop supply chain. Author further implemented this model to evaluate the supply chain performance of a case automotive industry in Malaysia. Jothimani and Sarmah (2014) developed a Supply Chain Operations Reference (SCOR) model and identified key performance indicators (viz. reliability, responsiveness, flexibility, cost measures etc.) (KPIs) for the service-oriented sector namely a third-party logistics (3PL) service provider. Authors further, applied F-AHP and TOPSIS in integration with SCOR for measuring the Supply Chain Performance (SCP) in light of a real life case company.

Sari et al. (2014) proposed a fuzzy multi-criteria evaluation procedure for measurement of supply chain performance. Authors further used Fuzzy DEMATEL to prioritize the performance measurement criteria (viz. on time delivery, satisfying industry regulations, cost minimization, quality, technical capability etc.) of supply chain.

### 2.4.2 Performance Evaluation of Green Supply Chain

In this era of industrialization, supply chain network activities may cause considerable hazards to the environment due to air emissions, carbon footprint, discarded packaging materials, scrapped materials, residuals etc. To save the environment from these harmful consequences, green supply chain management has been introduced and recognized as an environmental innovation. Green supply chain management has become an important avenue in current business scenario and is committed to eradicate environmental pollution from the supply chain network activities. More specifically, GSCM is conceptualized to integrate environmental thinking into traditional supply chain management (Chin et al., 2015; Rao, 2006; Srivastava, 2007).

It is hereby observed that the implementation of green concepts in the organizational supply chain management indeed requires a performance evaluation process. Such kind of evaluation may definitely help the organizations to evaluate their existing status of green performance practices. The performance measurement approach, in addition to the traditional financial performance and accounting measures, aids in firm's decision making with regard to the overall organizational goal. In this sense, (Zhu and Sarkis, 2004) examined the relationships between green supply chain management practice and environmental and economic performance. Using moderated hierarchical regression analysis, the authors evaluated the general relationships between specific GSCM practices and performance. The authors then investigated how two primary types of management operations philosophies, quality management and just-in-time (or lean) manufacturing principles influenced the relationship between GSCM practices and performance. Hervani et al. (2005) provided an integrative framework for study, design and thereof to evaluate the performance of green supply chain.

Kainuma and Tawara (2006) extended the range of the supply chain to include re-use and recycling throughout the life cycle of products and services. The authors proposed multiple attribute utility theory method for assessing performance of a supply chain. The authors considered this approach to be one of the 'the lean and green supply chain' methods. It was possible to evaluate the performance of a supply chain not only from a managerial viewpoint but also from an environmental performance viewpoint. Tsai and Hung (2009) proposed a Fuzzy Goal Programming (FGP) approach that integrated Activity Based Costing (ABC) to measure the performance of green supply chain along with supplier selection. Authors further used this model to measure the performance of green supply chain of a mobile phone company in Taiwan. Shepherd and Günter (2010) provided a taxonomy of performance measures followed by a critical evaluation of measurement systems designed to evaluate the performance of green supply chains.

Lin et al. (2011) evaluated the green criteria (viz. pollution control initiatives, use of environment friendly technology, environmental certification, increase of cost for purchasing environmentally friendly, quality improvement etc.) that had the great impact on the performance of an automobile manufacturing industry in Taiwan. The FST and DEMATEL were used together for the evaluation process. Authors further concluded that the increase of cost for purchasing environmentally friendly material was the most influential and significant criterion, while the pollution control initiatives was the most effective criterion. Olugu et al. (2011) developed a green supply chain performance assessment framework by considering automobile green supply chain as a two-in-one chain, to comprehensively and effectively establish the relevant measures. The two-in-one supply chain included a forward and backward chain for the considered case automobile industry in Malaysia. Large and Thomsen (2011) recognized five potential drivers of green supply management performance: green supply management capabilities, the strategic level of the purchasing department, the level of environmental commitment, the degree of green supplier assessment, and the degree of green collaboration with suppliers. These constructs were used to form a structural model explaining the environmental performance and the purchasing performance. The model was analyzed with Smart PLS 2.0 using data collected from a group of German purchasers.

Azevedo et al. (2011a) investigated the relationships amongst green practices of supply chain management and supply chain performance in the context of an automotive company. A theoretical framework was proposed in order to explore the influence of green practices (viz. environmental friendly practices in purchasing, environmental collaboration with suppliers, ISO 14001 Certification, minimizing waste, environmental collaboration with customers etc.) on SC performance (viz. efficiency, environmental cost, quality, business wastage, customer satisfaction etc.). Lee et al. (2012) explored green supply chain management practices and their relationship with organizational performance. This research focused on the effect of GSCM efforts and other organizational factors on firm performance of SMEs that served as suppliers to large customer firms in the electronics industry. This study developed a research model relating GSCM practice and business performance through three organizational variables (viz. employee satisfaction, operational efficiency, and relational efficiency) as moderators.

Dey and Cheffi (2013) suggested an analytical framework for evaluating the environmental performance of manufacturing supply chains using analytic hierarchy process. The developed framework integrated the supply chain processes (viz. supplier relationship management, internal supply chain management and customer relationship management etc.) with organizational decision levels (both strategic and operational). The proposed framework was applied to three selected manufacturing organizations in UK. Diabat et al. (2013) explored the practices and performances of the GSCM; considered the relationship between green supply chain practices (initiatives) and performance outcomes. In this paper, two questionnaires were developed and a survey was conducted to assess the importance of GSCM practices and performances in an automotive company in a developing country using a fuzzy multiple criteria decision making method. The result of this paper presented a practical guidance for managers in performing GSCM practices by ranking GSCM practices according to their importance which leads towards improving GSCM performances. Mirhedayatian et al. (2014) proposed a novel network DEA model for evaluating the GSCM in the presence of dual-role factors, undesirable outputs, and fuzzy data. Bhattacharya et al. (2014) evaluated the performance of green supply chain by applying an intra-organisational Collaborative Decision Making (CDM) approach. A fuzzy-ANP based Green Balanced Scorecard (GrBSc) was utilized within the CDM approach to support in arriving at a consistent, accurate and timely data flow across all cross-functional areas of a business.

Uygun and Dede (2016) developed a framework for the performance evaluation of green supply chain using integrated fuzzy multi-criteria decision making techniques. The cause and effect interrelationship between various GSCM dimensions (viz. green manufacturing/packaging, green marketing, environmental participation, green suppliers, green stock, and green eco-design etc.) were established using fuzzy

DEMATEL. Based on interrelationship, fuzzy ANP method was applied for determining the weights of the considered criteria (viz. regulations, environmental, performances, green manufacturing, green packaging, recycling, disposal etc.). Finally, fuzzy-TOPSIS was utilized in order to evaluate and to rank the GSCM performance of alternative companies.

### 2.4.3 Performance Evaluation of Resilient Supply chain

Current marketplace is potentially characterized by higher levels of turbulence and unpredictability. As a result, supply chains are vulnerable to disruptions. As a consequence, the risk to the business continuity has increased (Azevedo et al., 2008, Azevedo et al., 2011b). To overcome with certain system disruptions, the concept of resilient supply chain were developed by imposing some resilient paradigm into the traditional supply chain (Haldar et al., 2014). The focus of the resilient paradigms (Haimes, 2006) is as follows:

a) To recover to the desired state of the system that has been disturbed, within an acceptable period and at an acceptable cost.
b) To reduce the disturbance impact by changing the effectiveness level of a potential threat.

As, the major intention of SC resilience is to prevent the supply chain from undesirable state (i.e. failure); hence, performance evaluation of the resilient supply chain has become indeed necessary. Rose and Krausmann (2013) proposed an economic framework for the development of a resilience index for business recovery. The proposed framework comprise Computable General Equilibrium (CGE) analysis. Nikookar et al. (2014) developed a qualitative approach based on multi-criteria decision making approach to evaluate resilience capability supply chains. The case study was performed in three basic steps viz. identification of practices affecting resilience of the supply chain followed by a questionnaire survey and finally analysis of gathered data through a ‘sense and respond’ method.

### 2.4.4 Performance Evaluation of G-Resilient (Ecosilient) Supply Chain

G-resilient supply chain is an integration of green supply chain and resilient supply chain. Implementing g-resilient supply chain philosophy to the various organizations is an attempt to make the pollution free environment along with zero tolerance against supply chain disruptions. G-resilient supply chain is a recent development that comprised green as well as resiliency parameters; hence, their evaluation must be carried out to acquire the current status of supply chain's performance. In this regard (Azevedo et al., 2011c) attempted to evaluate g-resilient supply chain for "n" companies. Later on (Azevedo et al., 2013b) suggested an ecosilient index in order to assess the greenness and resilience of an automotive supply chain. The Delphi technique was used to weight the supply chain practices (viz. strategic stock, lead time reduction, flexible supply base/flexible sourcing, ISO 14001 certification, reuse/recycling materials etc.) according to their importance towards the automotive supply chain competitiveness. The developed model was applied to an automotive case company in Portugal. Moreover, and the inter-relationship between supply chain practices was explored by Interpretive Structural Modeling (ISM) approach.

## 2.5 Risk Assessment

Risk is the combination of asset (people, property, and information), vulnerability (weaknesses or gaps in a security program) and threats (anything that can exploit a vulnerability, intentionally or accidentally, and damage or destroy an asset) [Source: http://www.threatanalysis.com]. Risk may also be defined as a probability or threat of damage, injury, loss, or any other negative incident caused by external or internal vulnerabilities. Risk is inherently present in every step of life as well as in business activities and can be avoided through preemptive action like adaptation to an efficient risk management platform.

Risk management is the identification, assessment, and prioritization of risks followed by coordinated and economical application of resources to minimize, monitor, and control the probability of occurrence and also the impact of unfortunate events (Behret et al., 2011). As risk is inherently present everywhere: supply chain, supplier selection and e-commerce avenue etc. all are bearing some sort of risks. The work done by previous researchers towards the risk assessment in supply chain, supplier selection and e-commerce have been discussed in **Section 2.5.1** to **Section 2.5.3**.

### 2.5.1 Supply Chain Risk Assessment

Supply Chain Management (SCM) is defined as a set of strategies used to interconnect suppliers, manufacturers, warehouses and clients so that the merchandise is produced and distributed at the right quantities, to the right places at the right time with the objective of minimizing system costs and maximizing customer service levels (Simchi et al., 2000; Tuncel and Alpan 2010). In last two decades, supply chains are experiencing rapid technological change in the manufacturing and retail sector. As a matter of fact, business is becoming more risky because of increasing use of outsourcing, globalization of supply chains, and shorter product life-cycle (Christopher et al., 2011; Zhao et al., 2013).

In past few years, to ensure the process continuity, interactions between supplier and customer has got much more attention in academic discussion and commercial exercise. This is because of significant increment in the level of risks in supply chain. Apart from that, globalization, outsourcing and offshoring strategies, flow of information and goods, reduction of supplier base, central distribution, focus on efficiency rather than effectiveness and flexibility are some major reasons responsible for supply chain risk (Jüttner et al., 2003; Wieteska, 2013). Supply Chain Risk Management (SCRM) plays an important role towards management of business developments in a proactive way. Supply chain risk may have numerous sources (viz. process, control, demand, supply and environment etc.). Supply chain encountering risks needs precise and suitable responses such as techniques, attitude and strategies for assessment and mitigation of risks (Lavastre et al., 2012).

The risk factors of supply chain can be identified from areas namely: transport/distribution, manufacturing, order cycle, warehousing, and procurement. Risk is a diversified construct and can be defined in many ways depending on the area of research. Recently, supply chain activities have become highly risky due to several external and internal liabilities (viz. demand, supply, planning, control, environmental, social etc.) at every stage. Today's supply chains are under intense competitive pressure and have to face high levels of supply chain risks because of the complexity and the uncertainty associated with managing supply chain partners and processes, leading to supply chain risks (Knemeyer et al., 2009; Pettit et al., 2010; Cantor et al., 2014). Risk makes supply chains more complicated and more time sensitive than ever before; and, therefore, companies within a supply chain need to strategically cooperate with their key suppliers and customers to survive, compete, and prosper (Zhao et al., 2008). Globalization, e-trading, advanced technologies and emerging production techniques have increased supply chain's efficiency and added value. However, despite of numerous advantages, these factors make supply chains more fragile and vulnerable to risks (Kirilmaz and Erol, 2016).

Today, risk assessment is considered as utmost important to perform in order to maintain an uninterrupted supply chain performance and thereby to achieve various organizational goals. Hence, uncertainties involved in supply chain should not be overlooked. Since, supply chain risks have a significant impact on the operational, financial and market success of the firm; there is indeed a need to develop efficient methods for identifying, highlighting and addressing supply chain risks. In this context, application of Fuzzy Set Theory (FST) has been found quite fruitful to assess supply chain risks. Risk management is a process of identifying the risks associated with specific organization/firm and to treat them with an appropriate action. According to (Blackhurst and Wu, 2009), most of the Supply Chain Risk Management (SCRM) strategies include risk identification, risk analysis, risk management, and risk monitoring. Many past researchers carried out in depth analysis on supply chain risk assessment process and responded to risks with an appropriate way.

Christopher and Peck (2004) identified supply risk, demand risk, operational risk and security risk as the major supply chain risks and attempted to mitigate their severity by creating the supply chain more resilient. Author further, suggested a 'end-to-end' visibility to mitigate supply chain risk. Sinha et al. (2004) presented a generic prescriptive methodology for assessing and mitigating the aerospace supply chain risks. Furthermore, authors proposed the five activities in detail for Supply Chain Risk Management (SCRM) : recognition of risks, measurement of risks, development and implementation of solutions, conducting Failure Modes and Effects Analysis (FMEA) and continuously improvement. Faisal et al. (2006) presented a framework for supply chain risk mitigation by considering various enablers (viz. information sharing, trust among supply chain partners, collaborative relationships among supply chain partners, corporate social responsibility, strategic risk planning etc.) that support to mitigate risk in a supply chain network. Author further applied Interpretive Structural Modeling (ISM) to develop a hierarchy-based structure and to explore the mutual associations amongst various enablers of risk mitigation. Tang and Tomlin (2008) described supply risks, process risks, demand risks, intellectual property risks, behavioral risks, political/social risks as a six major types of supply chain risks that occur regularly. The authors proposed two effective mechanisms; i) based on risk avoidance concept (Poka-

Yoke system) and ii) based on some TQM (Total Quality Management) principles to reduce the likelihood of occurrence of certain undesirable events. Tuncel and Alpan (2010) proposed a Petri Net (PN) based modeling framework to model the supply chain network and to analyze the effects of various risks and mitigation actions on the overall system's performance. The proposed methodology was illustrated with a case study in food industry, Turkey.

Behret et al. (2011) stated five major risk sources (viz. transport/distribution, manufacturing, order cycle, warehousing, procurement) in the context of supply chain and developed a risk measurement model to minimize supply chain risks by the application of Fuzzy Inference Systems (FIS). Berenji et al. (2011) used Fuzzy Analytic Network Process (F-ANP) and fuzzy-TOPSIS for identifying and assessing supply chain risks at Mapna Boiler Engineering and Manufacturing Company, Iran. Thun and Hoenig (2011) empirically analyzed supply chain risk management practices based on a survey with few manufacturing plants in the German automotive industry. Diabat et al. (2012) identified various types of supply chain risk (viz. macro-level risks, demand management risks, supply management risks, product/service etc.) and further, developed a model to analyze the risks involved in a food supply chain by employing ISM approach.

Sofyalıoğlu and Kartal (2012) used Fuzzy Analytical Hierarchy Process (F-AHP) to determine the most important supply chain risks (viz. supply risk, demand risk, operational risk, security risk etc.) and the corresponding risk management strategies (postponement, speculation, hedging, control/share/transfer, security, and avoidance) for iron and steel industry in Turkey. Wang et al. (2012) proposed a risk assessment approach to perform structured analysis of aggregative food safety risk in the food supply chain by using the concepts of fuzzy set theory and analytical hierarchy process. Ganguly and Guin (2013) proposed fuzzy-AHP approach to determine the supply related risks (viz. on time delivery, order correctness, order completeness, damage and defect free and cost etc.) and its potential impact on the buyer organization.

Samvedi et al. (2013) developed an integrated approach, with F-AHP and F-TOPSIS towards quantifying risks (supply risk, demand risk, process risk and environmental risk) in a supply chain and then consolidating the values into a comprehensive risk index. Mangla et al. (2014a) focused on the operational green supply chain risk evaluation and management. The uncertainty involved was evaluated by means of

Monte Carlo Simulation to demonstrate the delay/disturbance consequences of the risk. Aqlan and Lam (2015) presented an integrated framework for supply chain risk assessment that contained three main components: survey, Bow-Tie analysis, and Fuzzy Inference System (FIS). The proposed framework was demonstrated in a high-end server manufacturing environment based on the outsourcing of parts from various suppliers in different geographical localities.

Ramkumar (2016) applied modified ANP (Analytical Network Process) and FIS for risk assessment of in-house and third party e-procurement systems. Yu et al. (2016) explored the risk management strategy for the dairy supply chain in China by conducting semi-structured interviews with various supply chain experts working in the said dairy company. The risk identified thereof (viz. supply risk, demand risk, operational and control risk, environmental risk etc.) have been categorized by Failure Mode Effect Analysis (FMEA) framework. In relation to the inventory management it was observed in the literature that organizations do encounter challenges in managing inventory because of two distinctive supply chain risk factor mostly: demand exceeds supply (supply risk) lead to a situation of stock out and supply exceeds demand (inventory risk) resulting in surplus inventory (Craighead et al., 2007; Zepeda et al., 2016).

### 2.5.2 Suppliers Selection Considering Risk

Supplier selection is a process of selecting the best supplier amongst the available supplier alternatives. This process is usually performed by various organizations to outsource the material and services. For many years, supplier selection has been a key concern for researchers and practitioners as well. In past few years, some undesired incidents (like terror attack, natural disasters, stakeholders strike etc.) have been noticed frequently. As a consequence, supplier selection process have become more difficult and risky, causing some supply chain disruptions and supplier failure. To deal with such kind of unexpected situations in a constrained environment, a risk based supplier selection framework is indeed required and to be implemented across the organizations seeking supplier’s selection under risk. As of now, so many authors tried to develop a risk based supplier evaluation framework and applied into a suitable firm/industry to illustrate their model.

Chan and Kumar (2007) discussed about the risks (viz. political stability risk, economic risk, geographical location risk, Terrorism etc.) involved in a supplier selection process. A fuzzy based analytic hierarchy process was developed which could tackle the various risk factors involved in the selection of global supplier in the current business environment. The developed model was applied to a manufacturing firm seeking the best international supplier. Wu and Olson (2008) developed three types of evaluation framework by using Monte Carlo simulation namely Chance Constrained Programming (CCP), Data Envelopment Analysis (DEA), and Multi-Objective Programming (MOP) in order to perform supplier selection process under risk. Meena et al. (2011) proposed an Expected Total Cost (ETC) based framework to perform the supplier selection process under risk. The model was designed considering catastrophic events of disruption (supply risk), that might result in supplier failure. Nourbakhsh et al. (2013) suggested a model to select suppliers in consideration with supply risks. In the suggested framework, based on some proposed risk sources, experts were asked first to define the reliabilities (supply risks) of procurement elements (viz. production, communication, transportation etc.). Then, a competent Multi-Layer Perceptron (MLP) was used to calculate the reliability scores. DEA was applied to tackle traditional supplier selection criteria (viz. price, delivery, quality and capacity etc.). Finally, based on efficiencies and reliability score, a set of Pareto-optimal suppliers was articulated.

Hamdi et al. (2014) suggested Stochastic Mixed Linear Program (MILP) approach for the selection of suppliers under risk disruption. Two sets of disruption situations were considered: (1) independent local disruption of suppliers (2) global disruption of suppliers. Value at Risk (VaR) along with Conditional Value at Risk (CVaR) were conceptualized to model the risks of supply chain. Li and Zeng (2016) proposed a supplier selection model that utilized the Failures Modes and Effects Analysis (FMEA) to assess the risks in the decision process. The developed framework was demonstrated for risk analysis through a case study (i.e. selection of methanol supplier).

### 2.5.3 E-Commerce Risk Assessment

Electronic Commerce (EC) or e-commerce is an internet based commercial platform that includes transfer of capital, information, material, services and data. Nowadays, E-commerce has become the fastest growing business that offers online trading (i.e. buying or selling) facilities at minimum possible time with better quality of the product.

E-commerce also allows consumers to exchange goods or services, electronically without no usual barriers like geographic limitation, delay in service etc. E-commerce has got an astonishing growth from last few years; and supposed to be continued at the same rate or even more. Since every activity has a flip side of its own development (i.e. risks in procurement); e-commerce is also affected by some sort of risks. E-commerce possesses diversity of commercial activities with innovative technology driver; and these may come with both benefit and risk. As e-commerce risk like online fraud, data hijacking, unauthorized transactions, fake calls to the consumers asking their bank details are experienced much frequently; e-commerce risk assessment has become an important area of research in recent management studies.

Viehland (2001) attempted to manage business risk in e-commerce and suggested that risks in relation to EC development are the risks of direct or indirect loss to the organization in development (involving planning, analysis, design and implementation). Park et al. (2004) the provided an e-commerce Adoption Model (e-CAM) for the adoption opportunity of e-commerce. E-CAM integrates the technology acceptance model with the philosophies of perceived risk to explain the e-commerce adoption.

Torrellas et al. (2004) developed a framework for Multi-Agent System Engineering by applying Ontology Domain Modelling (ODM) for risk assessment in e-commerce services. Ngai and Wat (2005) outlined a methodology for the assessment of risks associated with e-commerce development using fuzzy set theory. A Web-based prototype Fuzzy Decision Support System (FDSS) was proposed to assist e-commerce project managers to identify potential e-commerce risk factors. Wat et al. (2005) empirically studied potential risks associated with e-commerce development using exploratory factor analysis. The analysis explored few major dimensions of risk related with e-commerce development namely requirements risk, client-server security risk, managerial risk, physical security risk, legal risk, vendor quality risk etc. Khokhar et al. (2006) recognized potential risk factors in relation to EC projects (viz. resources risk, requirements risk, vendor quality risk, client-server security risk, legal risk, managerial risk, outsourcing risk, physical security risk, cultural risk, re-engineering risk etc.) and developed an extended decision support system in integration with Dempster-Shafer (DS) theory in order to evaluate EC project risks. Kim et al. (2008) discussed whether trust and risk were responsible for an internet consumer’s purchase decision. To explore this, authors developed a theoretical model describing the trust based decision making process. The proposed model was tested using a Structural Equation Modeling technique based on the data collected via Web survey.

Zhang et al. (2012) investigated few e-commerce security factors (viz. data backup and restore, web server security, Operating System (OS) security, database security, identity authentication etc.) and suggested a model to support e-commerce experts towards effective assessment of e-commerce security. The proposed model was based on AHP and Dempster–Shafer (DS) theory of evidence. Ergu et al. (2014) proposed a maximum eigenvalue threshold as a consistency index for the Analytical Network Process (ANP) towards the risk measurement in decision analysis. The suggested threshold was statistically equivalent to the Consistency Ratio (CR).

## 2.6 Motivation and Objectives

Foregoing sections have illustrated prior state of art on various aspects of industrial decision making specifically in relation to robot selection, g-resilient supplier selection, 3PL service provider selection, supply chain performance assessment, risk assessment in e-commerce exercise etc. The necessity of establishing as well as implementing effective decision making tools in relation to aforesaid domains has well been understood. Decision making is definitely a complex task to accomplish due to subjectivity involved in the available dataset in regards of vague evaluation indices. Since, subjective human judgment do contain vagueness as well as ambiguity; conventional MCDM tools and techniques, that are capable dealing with objective (quantitative) data only, are found to be inefficient to operate in real world complex decision making scenarios.

Literature depicts extensive exploration of fuzzy set theory/fuzzy logic and grey set theory to provide a rational solution in the context of decision making where subjective human thought is the only way of representation for the exact situations. Based on the survey of past literature, it is concluded that fuzzy set theory and grey set theory are capable enough to tackle imprecision, incompleteness as well as inconsistency involved in the human judgment (Decision-Makers' response) by transforming those subjective (qualitative) data into an appropriate (fuzzy/grey based) mathematic base. The present work has intended to investigate the application potential of fuzzy/grey set theory based decision support frameworks towards selection of an appropriate robot, g-resilient supplier selection, 3PL service provider selection, g-resilient supply chain’s performance assessment. The work also has aimed to identify ill-(poorly) performing g-resilient supplier selection areas which need to be improved further in order to enhance overall performance level of the corresponding supplier.

The study has been extended further to perform fuzzy based risk analysis in e-commerce in a business context. The identified e-commerce risks have been evaluated and categorized into some distinct levels of severity. Additionally, an appropriate risk mitigation strategy has been recommended. An ISM approach has also been applied to explore the structural relationships amongst various risk sources (risk factors) that can adversely affect company’s e-commerce performance.

Based on the extensive literature survey, following research gaps have been observed and pointed out below:

1. In the context of decision making involving objective and subjective criteria both; past researchers have either transformed the subjective data into the objective data; or transformed objective data into subjective (fuzzy) representations for establishing a final decision. In this sense, a systematic decision support framework needs to be developed which can tackle the subjective (qualitative) as well as objective (quantitative) data simultaneously without changing their natural or original form of representation (identity) for effective industrial decision making.

2. Better exploration of decision making tools to consider the risk bearing attitude of the Decision-Makers’ is indeed a necessity.

3. Supplier selection is one of the most studied areas in the literature. Despite of the relevancy of the subject, organizations are still facing difficulties to perform supplier selection effectively. Supplier selection is a decision making task involving objective (quantitative) and subjective (qualitative) evaluation criteria. Quantitative criteria can easily be dealt with traditional decision making tools and techniques. However, decision making information in regards of ill (vaguely)-defined subjective criteria is basically confusing. In order to overcome this, traditional decision making approaches have been extended to operate under fuzzy environment to solve a variety of supplier selection

problem. Application of fuzzy set theory has proved its efficacy in dealing with imprecise and vague decision information in the ambiguous environment (Zadeh, 1965). Thus, traditional decision making approaches have been extended to operate under fuzzy environment to solve a variety of supplier selection problem. Plenty of literature is readily available highlighting application of classical/conventional fuzzy set theory embedded with different decision making techniques (Bevilacqua et al., 2006; Lin, 2012; Amid et al., 2006; Chen et al., 2006; Aksoy et al., 2014; Dalalah et al., 2011; Sanayei, et al., 2010; Kannan et al., 2013; Igoulalene et al., 2015; Díaz-Madroñero et al., 2010). As noted in literature, due to increased environmental awareness, apart from the tradition supplier selection criteria (viz. quality, cost, reliability, service etc.), green image and green capabilities of suppliers' must be considered during the selection process. Moreover, today's global business environment necessitates suppliers possessing resiliency practices (to cope up with disruptions/disturbances etc.). In this context, g-resilient performance assessment of candidate suppliers' has become indeed a necessity. Limited attempt has been made by the previous researchers to focus issues related to supplier selection considering 'green' as well as 'resiliency' criteria simultaneously.

4. 3PL logistic service provider selection has been attempted in numerous reporting; however, it has been noticed that decision making tools intended to solve 3PL provider problem need to be expanded further with grey numbers set theory, as it has been recommended by many authors that grey theory can flexibly deal with the fuzziness situation.

5. Supply chain is acting like a backbone for the organizations. Hence, their performance evaluation must be carried out to check their current status and to identify the factors responsible for the supply chain failures (or poor performance). Many authors have attempted to evaluate performance of traditional supply chain, green supply chain, lean supply chain, agile supply chain, sustainable supply chain and resilient supply chain, separately. However, literature has depicted that rare attempt has been made in integrating 'green' as well as 'resiliency' performance indices/criteria to compute a unique g-resilient (ecosilient) performance index of company's supply chain.

6. In relation to the risk analysis involved in e-commerce exercises; apart from probabilistic theory of risk analysis; it has been found that fuzzy based risk analysis has rarely been attempted. In this sense, an integrated risk evaluation approach in decision making perspective needs to be developed for the assessment, control and mitigation of the risks in an effective manner.

The dissertation presented here is intended to accomplish empirical research as well as case study to examine procedural steps of different decision support framework like Fuzzy-PROMETHEE, Fuzzy-TODIM, Grey-TODIM, Fuzzy-TOPSIS, Fuzzy-VIKOR, Fuzzy Risk Analysis etc. towards facilitating industrial decision making. The specific objectives of the present work have been delineated below.

1. To develop efficient decision support systems using fuzzy as well as grey numbers set theories. Exploration of Fuzzy-TODIM, Grey-TODIM and Fuzzy extended PROMETHEE etc. have been attempted herein. This has been articulated through different robot selection problems.

2. To propose a decision making framework that can integrate 'green' and 'resiliency' criteria both for the g-resilient supplier selection and, thereof, to compute a unique performance score (g-resilient index).

3. To develop a new decision support framework by using the basic concepts of dominance (adapted from the theory of TODIM) in conjugation with the grey numbers set theory. This has been articulated through a '3PL service provider selection' problem.

4. To establish a performance evaluation index platform in perspectives of Fuzzy Multi-Criteria Group Decision Making (FMCGDM) towards obtaining an equivalent unique 'g-resilient/ ecosilient' performance index of a case automotive supply chain.

5. To suggest a framework for in-depth understanding and assessment of e-commerce risks and to provide an overall risk extent/score ('crisp risk extent') through application of Fuzzy Set Theory (FST), Fuzzy Inference System (FIS) and Interpretive Structural Modeling (ISM).

# Chapter 3

# Selection of Industrial Robot

## 3.1 TODIM Based Decision Making Approaches towards Robot Selection

In the present work, MCDM problem towards selection of industrial robots has been articulated to examine decision outcome through logical exploration of TODIM *(Tomada de Decisión Inerativa Multicritero)* approach. However, it seems that application of crisp-TODIM has been addressed abundantly by previous researchers (for instance refer: Gomes and Rangel, 2009; Gomes et al., 2009). Since, traditional TODIM (crisp-TODIM) fails to solve decision making problems that encounter subjective data set, the further extension of TODIM is need to be explored for its variety of application in decision making domains. As said, the extension of crisp TODIM with fuzzy numbers set theory as well as grey numbers set theory has been attempted in this chapter. **Section 3.1.1** exhibits the application potential of TODIM in combination with fuzzy numbers set theory for the robot selection decision making while; **Section 3.1.2** provides an integrated decision making framework for robot selection through crisp-TODIM combined with grey numbers set theory.

## 3.1.1 Extension of TODIM for Decision Making in Fuzzy Environment: A Case Empirical Research on Selection of Industrial Robot

### 3.1.1.1 Coverage

In order to facilitate decision making in robot selection problem, in this part of work, an efficient fuzzy based Multi-Criteria Decision Making (MCDM) tool has been highlighted. TODIM coupled with Generalized Fuzzy Numbers (GFNs) set theory (fuzzy-TODIM) has been utilized here to determine the most preferable robot among all possible candidate alternatives. The results obtained thereof, have been compared to that of existing fuzzy-TOPSIS technique. A new formulation of fuzzy-TODIM (F-TODIM) by exploring the concept of similarity measure (between two fuzzy numbers) has been proposed herein in order to compute relative gain and loss for alternative pairs with respect to a particular criteria has been proposed in this part of work. Similar ranking order of the alternative robots as obtained (in comparison with the F-TODIM formulation based on fuzzy distance measure) concludes that fuzzy degree of similarity can fruitfully be utilized to evaluate dominance between two alternatives.

### 3.1.1.2 Background and Problem Statement

An industrial robot is a reprogrammable multifunctional manipulator designed to move materials, parts, tools or other devices by means of variable programmed motions and to perform a variety of other tasks. Industrial robots can perform repetitious, difficult and hazardous tasks (like assembly, machine loading, material handling, spray painting and welding) with precision, and can also significantly improve quality and productivity of the manufacturing organizations (Athawale and Chakraborty, 2011). According to (Athawale et al. 2010), control resolution, accuracy, repeatability, load carrying capacity, degrees of freedom, man-machine interfacing ability, programming flexibility, maximum tip speed, memory capacity and supplier's service quality are the most important attributes to be taken into account while selecting a robot for a particular industrial application. Many potential robot selection attributes (or criteria), e.g. cost, load capacity, man–machine interface, availability of diagnostic software, etc. must be considered for the selection of a particular robot (Huang and Ghandforoush, 1984; Jones et al., 1985; Offodile et al., 1987; Offodile and Johnson, 1990; Liang and Wang, 1993). In general, these attributes can be classified into two categories (Liang and Wang, 1993):

1. **Objective attributes** – these attributes are defined in numerical terms, e.g. cost, reliability, load capacity, repeatability, and positioning accuracy
2. **Subjective attributes** – these attributes have qualitative definitions, e.g. vendor's service contract, training, man-machine interface, and programming flexibility.

While selecting a robot for an industrial application, the decision-maker needs to consider all these attributes, where a tradeoff between them and the robot performance measures is indeed felt necessary. Selection of an appropriate robot for a particular industrial application is a typical Multi-Criteria Decision Making (MCDM) problem. Several approaches for robot selection have already been proposed by the past researchers (Bhangale et al., 2004; Goh et al., 1996; Khouja and Booth, 1995; Khouja, 1995; Zhao et al., 1996; Baker and Talluri, 1997; Goh, 1997; Parkan and Wu, 1999; Rao and Padmanabhan, 2006; Kahraman et al., 2007; Karsak, 2008; Chakraborty, 2011), which include the application of MCDM methods (Nnaji and Yannacoupoulou, 1988), production system performance optimization models (Abdel-Malek, 1986; Mehrez and Offodile, 1994), computer-assisted models (Offodile et al., 1987; Agrawal et al., 1991) and statistical models (Booth et al., 1992). Many precision-based methods for robot selection have also been developed (Huang and Ghandforoush, 1984; Offodile and Johnson, 1990; Imany and Schlesinger, 1989).

Most of the aforesaid methods developed earlier are based on the concepts of accurate measurement and crisp evaluation (Chu and Lin, 2003), i.e. the measuring values must be exact (numeric score). However, in real life situations, measures of subjective attributes (e.g. man–machine interface and programming flexibility) may not be precisely defined by the decision-makers i.e. these cannot be expressed by crisp numbers. Moreover, the evaluation of robot suitability versus subjective criteria and the weights of the criteria are usually expressed in linguistic terms (Liang and Wang, 1993;

Zadeh, 1975), as per individual's perception of the decision-makers (experts). Koulouriotis and Ketipi (2011) developed a fuzzy digraph method by considering various robot selection attributes and their relative importance for the optimum representation of interrelations in evaluation and selection of a robot. Chu and Lin (2003) proposed a fuzzy TOPSIS method for robot selection. Karsak (2008) introduced a decision model for robot selection based on quality function deployment (QFD) and fuzzy linear regression. Wu (1990) presented a decision support system based on the fuzzy set theory to aid the manager in the selection of a preferred robot for a particular application. Devi (2011) aimed at solving multiple-criteria decision making problems in relation to robot selection by exploring VIKOR method extended in intuitionistic fuzzy environment; in which the weights of criteria and ratings of alternatives were taken as triangular intuitionistic fuzzy set.

In order to improve product quality and increase productivity, robot selection has always been an important issue for manufacturing companies. The robot selection criteria data set may be objective, subjective or combination of both. Due to involvement of a large number of subjective attributes (evaluation criteria), robot selection decision making often relies on expert judgment of the decision making group regarding performance extent of evaluation criteria as well as priority weight of criteria. However, subjectivity of linguistic human judgment is often vague, imprecise and incomplete in nature.

Fuzzy logic (Zadeh, 1965; Kapoor and Tak, 2005) has the capability of dealing with such inconsistent evaluation information efficiently. Given the uncertain, ambiguous, and vague nature of robot selection criteria information, it requires the application of fuzzy based Multi-Criteria Decision Making (MCDM) methods for effective decision making. Variety of decision making tools and techniques have extensively been documented in literature to solve different kinds of industrial decision making problems. Traditional decision making approaches (that consider only crisp data) have been extended to operate in fuzzy environment. Fuzzy-AHP, Fuzzy-TOPSIS, Fuzzy-VIKOR, Fuzzy-PROMETHEE, Fuzzy-ELECTRE, Fuzzy-MOORA and many others have been applied to solve decision making problems in uncertain (fuzzy) environment. However, it has been observed that application of TODIM (*Tomada de Decisión Inerativa Multicritero*) has got limited usage in this context.

The specialty of TODIM method lies in the fact that it explores a global measurement of value calculable by the application of the paradigm of nonlinear Cumulative Prospect Theory (CPT). The method is based on a description, proved by empirical evidence, of how decision-makers' effectively make decisions in the face of risk. It has been noted that most of the existing MCDM tools are unable to capture or take into account the risk attitude/preferences of the decision maker. Prospect theory developed by (Kahneman and Tversky, 1979) is a descriptive model of individual decision making under condition of risk. Later, (Tversky and Kahneman, 1992) developed the cumulative prospect theory, which captures psychological aspects of decision making under risk. In the prospect theory, the outcomes are expressed by means of gains and losses with respect to a reference alternative (Salminen, 1994).

The value function in prospect theory assumes the S-shape concave above the reference alternative, which reflects the aversion of risk in face of gains; and the convex part below the reference alternative reflects the propensity to risk in case of losses (Krohling and Souza, 2012). In TODIM, first, each shape characteristic of the value function models psychological processes; the concavity for gains describes a risk aversion attitude, the convexity describes a risk seeking attitude; secondly, the assumption that losses carry more weight than gains is represented by a steeper negative function side (Gomes et al., 2013). Thus, CPT is a model for descriptive decisions under risk. As Ordinary Prospect Theory (OPT), CPT treats gains and losses separately. Basically CPT considers: (i) the evaluation of possible outcomes relative to a certain reference point (often the *status quo*); (ii) different risk attitudes towards gains (i.e. outcomes above the reference point) and losses (i.e. outcomes below the reference point) and care generally more about potential losses than potential gains (loss aversion); and (iii) a tendency to overweight extreme, but unlikely events, but underweight 'average' events (Gomes et al., 2013).

Existing literature supports that the prospect theory has successfully been used as behavioral model of decision making under risk mainly in economics and finance (Dhami and AlNowaihi, 2007; Gurevich et al., 2009). Unfortunately, the application of prospect theory to MCDM problems has been rarely attempted. The first MCDM method based on prospect theory was proposed by (Gomes and Lima, 1992). In the original mathematical formulation of TODIM (an acronym in Portuguese for Iterative multi-criteria decision making), the rating of alternatives, which composes the decision matrix, is represented by crisp values (crisp-TODIM). The TODIM method has many similarities with the PROMETHEE method; whereas, the preference function as computed in PROMETHEE is replaced by the prospect function. The TODIM method has been applied to rental evaluation of residential properties (Gomes and Rangel, 2009). In another reporting, (Gomes et al., 2009) reported application of the TODIM based MCDM approach for natural gas destination in Brazil.

However, aforesaid formulation of crisp-TODIM is unable to tackle subjective evaluation data. Hence, traditional TODIM needs to be extended further so that benefits of utilizing fuzzy set theory, to tackle incomplete and uncertain decision making information (subjective human judgment), can be well articulated. In this work, the ranking order of all alternative robots has been obtained taking into account of different robot selection attributes (subjective and objective attributes both); the work hence aims at extending the crisp-TODIM for linguistic reasoning under group decision making. Empirical result proves the applicability of this MCDM method to solve such type of complex industrial decision making problems. Procedural hierarchy and application potential of the fuzzy based TODIM approach has been illustrated in detail in this part of work. A comparative analysis has also been made with respect to an existing decision making tool i.e. Fuzzy-TOPSIS.

### 3.1.1.3 Research Methodology

In this study, TODIM method has been extended to work under fuzzy environment. The operational rules adapted from fuzzy numbers set theory have been integrated with the formulation of traditional TODIM (crisp-TODIM). Two case empirical studies have been demonstrated here. The first one considers all subjective robot selection attributes and the second one considers a data set consisting of subjective as well as objective attributes. The ranking order obtained through F-TODIM has been compared to that of fuzzy-TOPSIS. The work has been extended further to utilize the concept of fuzzy degree of similarity (instead of fuzzy distance measure) to estimate dominance between two alternatives with respect to a particular criterion. For this purpose, F-TODIM formulations have been modified accordingly.

#### 3.1.1.3.1 Preliminaries on Prospect Theory

The value function used in the prospect theory is described in form of a power law according to the following expression (Kahneman and Tversky, 1979):

$$v(x) = \begin{cases} x^{\alpha} & \text{If } x \geq 0 \\ -\theta(-x)^{\beta} & \text{If } x < 0 \end{cases} \tag{3.1}$$

Here $\alpha$ and $\beta$ are parameters related to gains and losses, respectively. The parameter $\theta$ represents a characteristic of being steeper for losses than for gains. In case of risk aversion $\theta > 1$. Fig. 3.1 shows a prospect value function with a concave and convex S-shaped for gains and losses, respectively. (Kahneman and Tversky, 1979) experimentally determined the values of $\alpha = \beta = 0.88$, and $\theta = 2.25$, which are consistent with empirical data.

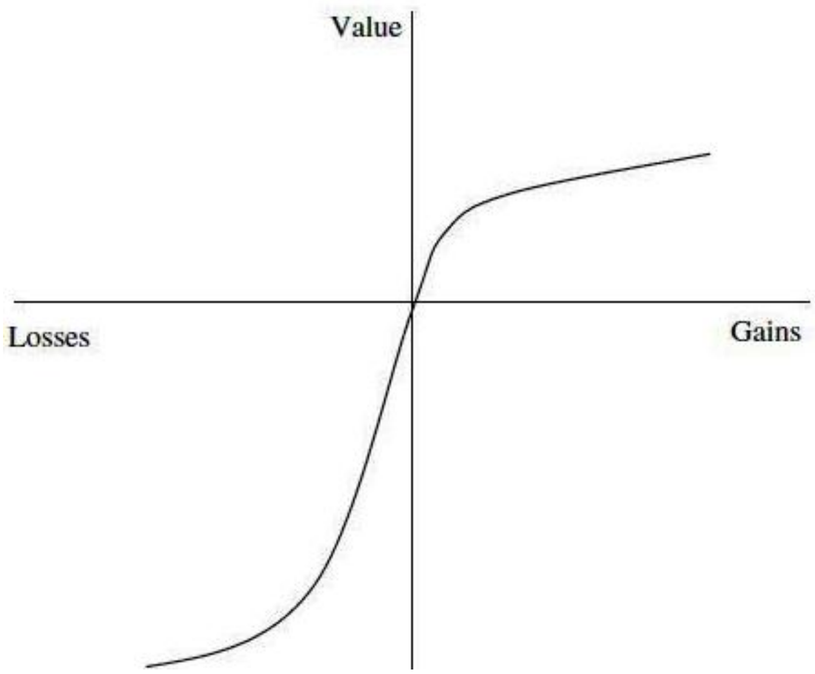


Fig. 3.1: Value function of the prospect theory (Gomes and Rangel, 2009)

### 3.1.1.3.2 Multi-Criteria Decision Making: The TODIM Method

Let us consider the decision matrix $\mathbf{A}$ which consists of alternatives and criteria, described by:

$$\mathbf{A} = \begin{array}{c} \\ A_1 \\ \ldots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & \ldots\ldots\ldots & C_n \end{array} \\ \begin{bmatrix} x_{11} & \ldots & x_{1n} \\ \ldots & \ldots & \ldots \\ x_{m1} & \ldots & x_{mn} \end{bmatrix} \end{array} \tag{3.2}$$

Here $A_1, A_2, \ldots, A_m$ are viable alternatives, and $C_1, C_2, \ldots, C_n$ are criteria, $x_{ij}$ indicates the rating of the alternative $A_i$ according to criteria $C_j$. The weight vector $\mathbf{W} = (w_1, w_2, \ldots, w_n)$ composed of the individual weights $w_j\,(j = 1,2,\ldots,n)$ for each criterion $C_j$ satisfying $\sum_{j=1}^{n} w_j = 1$. The data of the decision matrix $\mathbf{A}$ come from different sources, so it is necessary to normalize it in order to transform it into a dimensionless matrix, which allow the comparison of the various criteria. Assume that the normalized decision matrix is $\mathbf{R} = \lfloor r_{ij} \rfloor_{m \times n}$ with $i = 1,2,\ldots,m$ and $j = 1,2,\ldots,n$. After normalizing the decision matrix and the weight vector, TODIM begins with the calculation of the partial dominance matrices and the final dominance matrix. For such calculations the decision makers need to define firstly a reference criterion, which usually is the criterion with the height importance weight. So $w_{rc}$ indicates the weight of the criterion $c$ divided by the reference criterion $r$. Here, $w_{rc}$ is also called the trade-off rate (or trade-off weighting factor). Basically, TODIM is described in the following steps (Gomes and Lima, 1992; Gomes and Rangel, 2009):

**Step 1**: Calculate the final measure of dominance of each alternative $A_i$ over each alternative $A_j$ using the following expression:

$$\delta(A_i, A_j) = \sum_{C=1}^{m} \phi_C(A_i, A_j) \quad \forall (i, j) \tag{3.3}$$

Here,

$$\phi_c\left(A_i,A_j\right)=\begin{cases}\sqrt{\dfrac{w_{rc}\left(r_{ic}-r_{jc}\right)}{\sum\limits_{c=1}^{m} w_{rc}}} & If\ \left(r_{ic}-r_{jc}\right)>0\\ 0 & If\ \left(r_{ic}-r_{jc}\right)=0\\ -\dfrac{1}{\theta}\sqrt{\dfrac{\left(\sum\limits_{c=1}^{m} w_{rc}\right)\left(r_{jc}-r_{ic}\right)}{w_{rc}}} & If\ \left(r_{ic}-r_{jc}\right)<0\end{cases} \tag{3.4}$$

Here $r_{ic}$ and $r_{jc}$ are, respectively, the performances (normalized) of the alternatives $A_i$ and $A_j$ in relation to the particular criterion $c$. The term $\phi_c\left(A_i,A_j\right)$ is a reference function and it represents the contribution of the criterion $c$ to the function $\delta\left(A_i,A_j\right)$ when comparing the alternative $i$ with alternative $j$. The parameter $\theta$ represents the attenuation factor of the losses, which can be tuned according to the problem at hand. In the present work $\theta$ value has been assumed 1.

Different kinds of decision-makers can be understood in terms of their risk and loss attitude. Although the TODIM method does not deal with risk directly, the way the decision-maker evaluates the outcomes of any decision can be expressed by their risk attitude: for instance, a cautious decision maker will undervalue a superior result more than a braver one (Gomes et al., 2013). The attenuation factor $\theta$ in the TODIM method represents the risk aversion or propensity of the decision maker. It has been verified that fact that the different values for $\theta$ led essentially to the same ranking order indicate robustness of the results (Gomes et al., 2009). In Eq. (3.4), it can occur three cases:

(i) if the value $\left(r_{ic}-r_{jc}\right)$ is positive, it represents a gain;

(ii) if the value $\left(r_{ic}-r_{jc}\right)$ is zero, it represents neither gain nor loss;

(iii) if the value $\left(r_{ic}-r_{jc}\right)$ is negative, it represents a loss.

The final matrix of dominance is obtained by summing up the partial matrices of dominance for each criterion (Eq. 3.3). The relative measure of dominance of one alternative over another is found for each pair of alternatives. This measure is computed as the sum over all criteria of both relative gain/loss values for these alternatives. The parts in this sum will be either gains, losses or zeros, depending on the performance of each alternative with respect to every criterion (Gomes et al., 2009).

The function $\phi_c$ reproduces the value function of the Original Prospect Theory (OPT) and replicates the most relevant shape characteristics. That function fulfills the concavity for positive outcomes (convexity for negative outcomes), and second, it enlarges the perception of negative values for losses than positive values for gains, both value functions are steeper for negative outcomes than for positive ones (Gomes et al., 2013).

**Step 2**: Calculate the global value of the alternative $i$ by normalizing the final matrix of dominance according to the following expression:

$$\xi_i = \frac{\sum \delta(i,j) - \min \sum \delta(i,j)}{\max \sum \delta(i,j) - \min \sum \delta(i,j)} \tag{3.5}$$

Ordering the values $\xi_i$ provides the rank of each alternative. The best alternatives are those that have higher value $\xi_i$.

### 3.1.1.3.3 Preliminaries of Fuzzy Mathematics

**Definition 1**: A fuzzy set $\tilde{A}$ in a universe of discourse $X$ is characterized by a membership function $\mu_{\tilde{A}}(x)$ that assigns each element $x$ in $X$ a real number in the interval $[0,1]$. The numeric value $\mu_{\tilde{A}}(x)$ stands for the grade of membership of $x$ in $\tilde{A}$.

**Definition 2**: A triangular fuzzy number $\tilde{a}$ is defined by $\tilde{a} = (a_1, a_2, a_3)$ with membership function (Eq. 3.2) given by:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < a_1, \\ \dfrac{x - a_1}{a_2 - a_1}, & a_1 \le x \le a_2, \\ \dfrac{x - a_3}{a_2 - a_3}, & a_2 \le x \le a_3, \\ 0, & x > n_3. \end{cases} \tag{3.6}$$

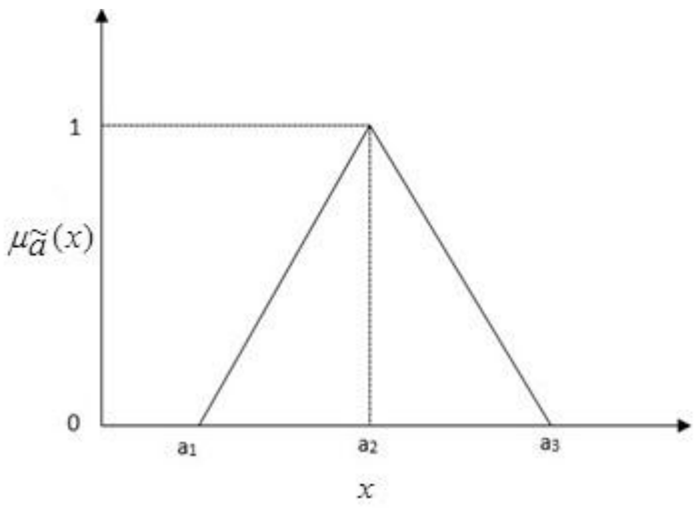


Fig. 3.2: Triangular fuzzy number $\tilde{a} \sim (a_1, a_2, a_3)$

**Definition 3**: Let a triangular fuzzy number $\tilde{a} = (a_1, a_2, a_3)$, then the defuzzified value $m(\tilde{a})$ is calculated by:

$$m(\tilde{a}) = \frac{(a_1 + a_2 + a_3)}{3} \tag{3.7}$$

**Definition 4**: Let two triangular fuzzy numbers $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$, then the operation with these fuzzy numbers are defined as follows:

1. Addition of fuzzy numbers (+)

$$\tilde{a} \oplus \tilde{b} = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{3.8}$$

2. Subtraction of fuzzy numbers (-)

$$\tilde{a}(-)\tilde{b} = (a_1 - b_1, a_2 - b_2, a_3 - b_3) \tag{3.9}$$

3. Multiplication of fuzzy numbers $\otimes$

$$\tilde{a} \otimes \tilde{b} = (a_1 b_1, a_2 b_2, a_3 b_3) \tag{3.10}$$

4. Division of fuzzy numbers $(/)$

$$\tilde{a}(/)\tilde{b} = (a_1 / b_3, a_2 / b_2, a_3 / b_1) \tag{3.11}$$

5. Multiplication by a scalar number $k$

$$k\tilde{a} = (ka_1, ka_2, ka_3) \tag{3.12}$$

**Definition 5**: Let two triangular fuzzy numbers $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$, then the distance between them is computed as (*vertex method*):

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}\left[(a_1 - b_2)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2\right]} \tag{3.13}$$

Also, $d(\tilde{a}, \tilde{b}) = d(\tilde{b}, \tilde{a})$ (3.14)

### 3.1.1.3.4 F-TODIM: Exploration of Fuzzy Distance Measure

The basics of prospect theory and TODIM method can be retrieved from **Section 3.1.1.3.1** and **Section 3.1.1.3.2**. The exploration of TODIM method in integration with fuzzy set theory is given below:

Let us consider the fuzzy decision matrix $\mathbf{A}$, which consists of alternatives and criteria, described by:

$$\mathbf{A} = \begin{array}{c} \\ A_1 \\ .... \\ A_m \end{array} \begin{array}{c} \begin{matrix} C_1 & .......... & C_n \end{matrix} \\ \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \cdots & \cdots & \cdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array} \tag{3.15}$$

Here, $A_1, A_2, ..., A_m$ are alternatives, $C_1, C_2, ...., C_n$ are criteria, $\tilde{x}_{ij}$ are triangular fuzzy numbers where $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, that indicates the rating of the alternative $A_i$ with respect to criterion $C_j$. The weight vector $\mathbf{W} = (w_1, w_2, ... w_n)$ composed of the individual weights $w_j (j = 1, 2, ..., n)$ for each criterion $C_j$ satisfying.

The fuzzy TODIM method, for short, F-TODIM, which is an extension of TODIM, is described in the following steps (Krohling and de Souza, 2012)

**Step 1**: The criteria are normally classified into two types: benefit and cost. The fuzzy decision matrix $\tilde{\mathbf{A}} = [\tilde{x}_{ij}]$ with $i = 1, 2, ..., m,$ and $j = 1, 2, ..., n$ is normalized which results the correspondent fuzzy decision matrix $\tilde{\mathbf{R}} = [\tilde{r}_{ij}]_{m \times n}$. The fuzzy normalized value $\tilde{r}_{ij}$ is calculated as:

Here $B$ and $C$ are the set of benefit criteria and cost criteria, respectively, and

$$\tilde{r}_{ij} = \left( \frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right), \quad j \in B; \tag{3.16}$$

$$\tilde{r}_{ij} = \left( \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), \quad j \in C; \tag{3.17}$$

$$\begin{aligned} c_j^* &= \max_i \ c_{ij}, \ \ if \quad j \in B; \\ a_j^- &= \min_i \ a_{ij}, \ \ if \quad j \in C. \end{aligned} \tag{3.18}$$

The normalization method mentioned above is to preserve the property that the ranges of normalized triangular fuzzy numbers belong to [0, 1].

**Step 2**: Calculate the dominance of each alternative $\tilde{A}_i$ over each alternative $\tilde{A}_j$ using the following expression:

$$\delta\left(\tilde{A}_i, \tilde{A}_j\right) = \sum_{c=1}^{m} \phi_c\left(\tilde{A}_i, \tilde{A}_j\right) \quad \forall (i, j) \tag{3.19}$$

Where,

$$\phi_c\left(\tilde{A}_i, \tilde{A}_j\right) = \begin{cases} \sqrt{\dfrac{w_{rc}}{\sum_{c=1}^{m} w_{rc}} . d\left(\tilde{x}_{ic}, \tilde{x}_{jc}\right)} & If \ \left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right] > 0 \\ 0, & If \ \left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right] = 0 \\ -\dfrac{1}{\theta} \sqrt{\dfrac{\sum_{c=1}^{m} w_{rc}}{w_{rc}} . d\left(\tilde{x}_{ic}, \tilde{x}_{jc}\right)} & If \ \left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right] < 0 \end{cases} \tag{3.20}$$

The term $\phi_c\left(\tilde{A}_i, \tilde{A}_j\right)$ represents the contribution of the criterion $c$ to the function $\delta\left(\tilde{A}_i, \tilde{A}_j\right)$ when comparing the alternative $i$ with alternative $j$. The parameter $\theta$ represents the attenuation factor of the losses, which can be tuned according to the problem at hand. In this expression, $m(\tilde{x}_{ic})$ and $m(\tilde{x}_{jc})$ stands for the defuzzified values of the fuzzy number $\tilde{x}_{ic}$ and $\tilde{x}_{jc}$, respectively. The term $d\left(\tilde{x}_{ic}, \tilde{x}_{jc}\right)$ designates the distance between the two fuzzy numbers $\tilde{x}_{ic}$ and $\tilde{x}_{jc}$, as defined in Eq. (3.13). Three cases can occur in Eq. (3.20):

i. if the value $\left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right]$ is positive, it represents a gain;

ii. if the value $\left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right]$ is zero, there is neither loss nor gain;

iii. if the value $\left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right]$ is negative, it represents a loss.

The final matrix of dominance is obtained by summing up the partial matrices of dominance of each criterion [refer to Eq. (3.19)].

**Step 3**: Calculate the global value of the alternative $i$ by normalizing the final matrix of dominance according to the following expression:

$$\xi_i = \frac{\sum \delta(i,j) - \min \sum \delta(i,j)}{\max \sum \delta(i,j) - \min \sum \delta(i,j)} \tag{3.21}$$

Ordering the values $\xi_i$ provides the rank of each alternative. The best alternatives are those that have higher $\xi_i$ value

#### 3.1.1.3.5 F-TODIM: Exploration of the Concept 'Fuzzy Degree of Similarity'

In fuzzy risk analysis, similarity measure is an important research agenda. It is mostly used in the field of pattern recognition. Some similarity measures between fuzzy numbers have been presented in existing literature (Chen, 1996; Chen and Chen, 2001; Hsieh and Chen, 1999; Lee, 1999). Most recently, Wei and Chen (2009) presented a method to calculate the degree of similarity between generalized fuzzy numbers. This method combines the concepts of geometric distance, the perimeter and the height of generalized fuzzy numbers for calculating the degree of similarity between generalized fuzzy numbers. The mathematical basis of the similarity measure as proposed by (Wei and Chen, 2009) has been presented below.

Assume that two generalized trapezoidal fuzzy numbers $\tilde{A}$ and $\tilde{B}$ where, $\tilde{A} = (a_1, a_2, a_3, a_4, w_{\tilde{A}})$ and $\tilde{B} = (b_1, b_2, b_3, b_4, w_{\tilde{B}})$, $0 \geq a1 \geq a2 \geq a3 \geq a4 \geq 1$, and $0 \leq b1 \leq b2 \leq b3 \leq b4 \leq 1$. Then, the degree of similarity $S(\tilde{A}, \tilde{B})$ between the generalized trapezoidal fuzzy numbers $\tilde{A}$ and $\tilde{B}$ is computed as follows:

$$S(\tilde{A},\tilde{B}) = \left(1 - \frac{\sum_{i=1}^{4} |a_i - b_i|_i}{4}\right) \times \frac{\min(P(\tilde{A}), P(\tilde{B})) + \min(w_{\tilde{A}}, w_{\tilde{B}})}{\max(P(\tilde{A}), P(\tilde{B})) + \max(w_{\tilde{A}}, w_{\tilde{B}})}, \tag{3.22}$$

where, $S(\tilde{A},\tilde{B}) \in [0,1]$; $P(\tilde{A})$ and $P(\tilde{B})$ are defined as follows:

$$P(\tilde{A}) = \sqrt{(a_1 - a_2)^2 + w^2{}_{\tilde{A}}} + \sqrt{(a_3 - a_4)^2 + w^2{}_{\tilde{A}}} + (a_3 - a_2) + (a_4 - a_1) \tag{3.23}$$

$$P(\tilde{B}) = \sqrt{(b_1 - b_2)^2 + w^2{}_{\tilde{B}}} + \sqrt{(b_3 - b_4)^2 + w^2{}_{\tilde{B}}} + (b_3 - b_2) + (b_4 - b_1) \tag{3.24}$$

$P(\tilde{A})$ and $P(\tilde{B})$ are denoted as the perimeters of the generalized trapezoidal fuzzy numbers of $\tilde{A}$ and $\tilde{B}$. The larger the value of $S(\tilde{A},\tilde{B})$ the more the similarity between the generalized fuzzy numbers $\tilde{A}$ and $\tilde{B}$. Wei and Chen (2009) also proved the properties of $S(\tilde{A},\tilde{B})$. The two important properties are as follows:

**Property 1:** Two generalized trapezoidal fuzzy numbers $\tilde{A}$ and $\tilde{B}$ are identical, if and only if $S(\tilde{A},\tilde{B}) = 1$. (3.25)

**Property 2:** $S(\tilde{A},\tilde{B}) = S(\tilde{B},\tilde{A})$ (3.26)

The above formulation is also valid for generalized triangular fuzzy number since a generalized triangular fuzzy number $(a,b,c)$ can also be represented by a generalized trapezoidal fuzzy number like $(a,b,b,c)$.

The concept of degree of similarity between two fuzzy numbers has been articulated in this part of work (instead of fuzzy distance measure) in the formulation of F-TODIM. Since partial dominance (between two alternatives) is measured by the evaluative difference between criterions values; and hence, instead of fuzzy distance measure, $(1 - S(\tilde{x}_{ic}, \tilde{x}_{jc}))$ could fruitfully be explored to measure the effective difference (dissimilarity) between the criteria values in order to compute relative gain or loss in the computational hierarchy of F-TODIM. Hence, [Eq. (3.20), in **<u>Section 3.1.1.3.4</u>**] has been modified as:

$$\phi_c\left(\tilde{A}_i,\tilde{A}_j\right)=\begin{cases}\sqrt{\dfrac{w_{rc}}{\sum\limits_{c=1}^{m} w_{rc}}.\left(1-s\left(\tilde{r}_{ic},\tilde{r}_{jc}\right)\right)} & If\ \left[m\left(\tilde{r}_{ic}\right)-m\left(\tilde{r}_{jc}\right)\right]>0\\ 0, & If\ \left[m\left(\tilde{r}_{ic}\right)-m\left(\tilde{r}_{jc}\right)\right]=0\\ -\dfrac{1}{\theta}\sqrt{\dfrac{\sum\limits_{c=1}^{m} w_{rc}}{w_{rc}}.\left(1-s\left(\tilde{r}_{ic},\tilde{r}_{jc}\right)\right)} & If\ \left[m\left(\tilde{r}_{ic}\right)-m\left(\tilde{r}_{jc}\right)\right]<0\end{cases} \quad (3.27)$$

Here, the term $s\left(\tilde{r}_{ic},\tilde{r}_{jc}\right)$ designates the degree of similarity between the two fuzzy numbers $\tilde{r}_{ic}$ and $\tilde{r}_{jc}$, as defined in Eq. (3.22); and the term $\left(1-s\left(\tilde{r}_{ic},\tilde{r}_{jc}\right)\right)$ can be treated as the degree of dissimilarity (measure of dominance) for an alternative w.r.t. other for a particular criterion.

### 3.1.1.4 Case Empirical Research: Selection of Industrial Robot

#### 3.1.1.4.1 Exploration of Subjective Data Set: Case Illustration I

In this part of work, a subjective data set has been explored to demonstrate application potential of F-TODIM approach. Results obtained thereof, has also been compared to that of Fuzzy-TOPSIS. The following robot selection attributes have been considered: Man-machine interface ($C_1$), Programming flexibility ($C_2$), Vendor's service contract ($C_3$), Purchase cost ($C_4$), Load capacity ($C_5$), and Positioning accuracy ($C_6$). Apart from purchase cost, remaining attributes have been assumed beneficial in nature. However, it seems that purchase cost and load carrying capacity are basically objective attributes (quantitative) and their exact data can be available from the robot manufacturer; however, in this analysis, these two attributes have been evaluated subjectively by the decision makers.

Literature supports that aforesaid two attributes have been considered as means of subjectivity in many fuzzy based decision support approaches (Vahdani et al., 2014; Rashid et al., 2014). Table 3.1 represents the list of robot selection attributes considered here. The definitions of various criteria/attributes have been given below.

**Vendor's service quality** refers to the level and variety of services offered by a robot vendor

**Programming flexibility** refers to a robot's ability to accept different programming codes.

**Purchase cost** involves purchase, installation and training costs

**Repeatability** is a robot's ability to repeatedly return to a fixed position

**Load capacity** is the maximum weight that a robot can lift

**Man-machine interface**: An interface which permits interaction between a human being and a machine.

**Positioning accuracy** (explored in the *Case Illustration II*) is the measure of closeness between the robot end effectors and the target point, and can usually be defined as the distance between the target point and the center of all points to which the robot goes on repeated trial.

Two different linguistic terms set (9-member) has been explored (as shown in Table 3.2) to evaluate priority importance (weight) of different robot selection attributes as well as appropriateness rating of various attributes with respect to the candidate alternatives (robots). The following linguistic terms set: {Absolutely Unimportant, AU; Highly Unimportant, HU; Unimportant, U; Rarely Important, RI; Less Important, LI; Fairley Important, FI; Important, I; Very Important, VI; Absolutely Important, AI} has been used to assign priority weight against different selection attributes. Similarly, the linguistic terms set: {Absolutely Low, AL; Very Low, VL; Low, L; Fairly Low, FL; Medium, M; Fairly High, FH; High, H; Very High, VH; Absolutely High, AH}has been used to rate different alternatives with respect to different selection attributes. Decision-Makers (DMs) have been instructed to utilize these linguistic variables to assign priority weight as well as appropriateness rating of various attributes. Linguistic (subjective) decision making data needs to be converted into appropriate fuzzy numbers before applying F-TODIM approach. Table 3.2 also represents a set of generalized positive triangular fuzzy numbers corresponding to the linguistic terminology designated to express priority weight as well as appropriateness rating of various robot selection attributes.

A group of ten decision-makers (DM1,…, DM10) has been involved in this decision making. DMs have been instructed to utilize aforementioned linguistic terms sets (Table 3.2) to express their expert judgment in relation to the robot selection decision making. Expert data (expressed in linguistic terms) in relation to attribute weight as well as attribute rating have been furnished in Table 3.3 and Table 3.4, respectively. In course of F-TODIM, aforesaid linguistic data needs to be transformed into appropriate fuzzy numbers as depicted in Table 3.2. The aggregated fuzzy weights as well as aggregated fuzzy ratings of various robot selection attributes have been computed and furnished in Table 3.3 and Table 3.4, respectively. The aggregation procedure has been described below.

Assume that a decision group has $K$ persons; then the importance of the criteria and the rating of alternatives with respect to each criterion can be calculated as:

$$\tilde{x}_{ij} = \frac{1}{K}\left[\tilde{x}_{ij}^{1} \oplus \tilde{x}_{ij}^{2} \oplus \ldots \oplus \tilde{x}_{ij}^{K}\right] \tag{3.28}$$

$$\tilde{w}_{j} = \frac{1}{K}\left[\tilde{w}_{j}^{1} \oplus \tilde{w}_{j}^{2} \oplus \ldots \oplus \tilde{w}_{j}^{K}\right] \tag{3.29}$$

Here $\tilde{x}_{ij}^{K}$ and $\tilde{w}_{j}^{K}$ are the rating and the importance weight of the $K^{th}$ decision maker. Thus, the initial fuzzy decision making matrix has been shown in Table 3.5. As robot selection attributes consist of benefit as well as cost criteria both; the aforesaid initial fuzzy decision making matrix needs to be normalized. Eqs. (3.16-3.18) have been used to normalize the initial decision making matrix. The normalized fuzzy decision matrix has been furnished in Table 3.6. Similar to the formulation of crisp-TODIM, F-TODIM explores crisp weight of the attributes. Eq. (3.7) has been used to compute crisp weight of various attributes as tabulated in Table 3.3. The crisp weight set appears as {0.64, 0.77, 0.76, 0.69, 0.71, 0.72} for attributes $C_1,\ldots, C_6$, respectively. In this computation, attribute $C_2$ corresponds to the highest weight and, therefore, treated as reference criterion/attribute. The relative weight set of different attributes $C_1,\ldots, C_6$ have thus been computed as {0.83, 1.00, 0.99, 0.90, 0.92, 0.94} as shown in Table 3.3.

In course of F-TODIM, the measure of dominance (for a particular criterion c) between two alternatives $\tilde{A}_i$ and $\tilde{A}_j$ is determined by $\phi_c\left(\tilde{A}_i, \tilde{A}_j\right)$ (Eq. 3.20), in which normalized fuzzy rating of alternative $\tilde{A}_i$ i.e. $\tilde{r}_{ic}$ is to be compared with the normalized fuzzy rating of alternative $\tilde{A}_j$ i.e. $\tilde{r}_{jc}$. Here, $\tilde{r}_{ic}$ and $\tilde{r}_{jc}$ is compared with the basis of their crisp score i.e. $m(\tilde{r}_{ic})$ and $m(\tilde{r}_{jc})$. Hence, crisp scores against normalized fuzzy attribute ratings corresponding to different alternatives have been computed and shown in Table 3.7. Similarly, in computing $\phi_c\left(\tilde{A}_i, \tilde{A}_j\right)$ (Eq. 3.20), the value of fuzzy distance measure between two alternatives (normalized fuzzy ratings for a particular criterion c), i.e., $d\left(\tilde{r}_{ic}, \tilde{r}_{jc}\right)$ needs to be computed. Thus, distance measures corresponding to each pair of alternatives with respect to different criteria have been computed as furnished in Table 3.8. Now, evaluative difference $\left|m(\tilde{r}_{ic}) - m(\tilde{r}_{jc})\right|$ between each pair of alternatives with respect to different criteria has been computed and shown in Table 3.9.

By exploring the information from Table 3.8 and Table 3.9, the partial matrices of dominance (Table 3.10) has been developed using (Eq. 3.20). The final matrices of dominance have then been computed (using Eq. 3.19) and furnished in Table 3.11. Finally, the global measures $(\xi_i)$ of candidate alternatives have been computed using (Eq. 3.21) and tabulated in Table 3.12. The ranking order of alternative robots appear as $A_1 > A_2 > A_3 > A_4$ (for $\theta = 1, 2.5$).

The ranking order of alternative robots as obtained through F-TODIM has been compared to that of Fuzzy-TOPSIS; a well-known decision making approach supported by existing literature (Chen, 2000; Wang and Lee, 2007; Mahdavi et al., 2008; Kaya and Kahraman, 2011). The working principal of TOPSIS is that the method determines an ideal solution as well as an anti-ideal solution. An ideal solution is one which maximizes all benefit criteria and minimizes all adverse (cost) criteria; whereas, an anti-ideal solution is one which minimizes all benefit criteria and maximizes all adverse criteria. The most appropriate alternative is one which is at closest distance from the ideal solution (alternative) and farthest distance from the anti-ideal solution (alternative).

When, traditional TOPSIS is extended to work under fuzzy environment, it is denoted as Fuzzy-TOPSIS which utilizes fuzzy weight as well as fuzzy rating of various selection criteria/attributes. The fuzzy-TOPSIS approach has been applied to the aforesaid robot selection problem; however, the difference between F-TODIM and fuzzy-TOPSIS is that F-TODIM considers crisp weight of the attributes; whereas, fuzzy-TOPSIS can directly utilize fuzzy weight of various criteria. Therefore, in course of F-TODIM, fuzzy weights of criteria have been defuzzified and the corresponding crisp scores have been explored for further analysis.

In fuzzy-TOPSIS, the data in relation to aggregated fuzzy weight of different robot selection attributes (Table 3.3) and aggregated fuzzy ratings of attributes against each alternative (Table 3.4) have been explored. Since all elements of fuzzy numbers that represent aggregated fuzzy ratings of criteria belong to the range [0, 1], these have not been normalized here. However, criteria-conflict (beneficial as well as adverse criteria) has been considered in due course while determining ideal solution as well as anti-ideal solution. Aggregated fuzzy ratings (Table 3.4) of different criteria have been multiplied with corresponding aggregated fuzzy rating (from Table 3.3); to construct weighted fuzzy decision making matrix (Table 3.13). The ideal and anti-ideal solutions ($A^*$, $A^-$, respectively) have been furnished in Table 3.14. The distance of each alternative with respect to ideal as well as anti-ideal solution has been determined and furnished in Table 3.15. Finally, a closeness coefficient $(CC_i)$ has been determined for each of the alternatives followed by which preference order of the alternatives has been evaluated (Table 3.16). The ranking order of alternative robots that appears through exploration of fuzzy-TOPSIS is $A_1>A_3>A_2>A_4$.

While comparing the results (ranking order of alternative robots) of F-TODIM to that of fuzzy-TOPSIS, it has been observed that for both the cases the appropriate alternative robot appears as $A_1$; whilst robot $A_4$ is the worst choice. Apart from the best as well as worst choice, the preference order of alternative robots $A_2$ and $A_3$ appears reverse in order for aforesaid two approaches. This is because the values of $\xi_i$ (in case of F-TODIM) and the values of $CC_i$ (in case of fuzzy-TOPSIS) for alternatives $A_2$ and $A_3$ are very close. Therefore, appropriate ranking order for alternative robots can be realized as $A_1>A_2{\sim}A_3>A_4$ for F-TODIM and fuzzy-TOPSIS both.

#### 3.1.1.4.2 Exploration of Subjective and Objective Data: Case Illustration II

In this specific robot selection problem, three candidate robots have been evaluated against six generalized criteria viz. Purchase cost ($C_1$), Load capacity ($C_2$), Repeatability ($C_3$), Man-machine interface ($C_4$), Programming flexibility ($C_5$) and Vendor's service contract ($C_6$). Amongst six selection attributes, first three ($C_1$, $C_2$, and $C_3$) have been assumed quantitative in nature and the evaluation data as reported by (Rao and Padmanabhan, 2006) have been reutilized here. Other three attributes ($C_4$, $C_5$ and $C_6$) have been evaluated subjectively by the expert group. In the known set of attributes, purchase cost ($C_1$) and Repeatability ($C_3$) are non-beneficial attributes while other attributes are treated as beneficial in nature. In this robot selection problem out of the six generalized criteria, Man-machine interface ($C_4$), Programming flexibility ($C_5$) and Vendor's service contract ($C_6$) are qualitative attributes that cannot be expressed directly by numeric scores; therefore, for resolving this intricate decision making problem, generalized triangular fuzzy numbers set theory has been introduced.

Table 3.17 represents the consolidated list of robot selection attributes considered here. Two different linguistic terms set (7-member) has been explored in Table 3.18 and Table 3.19, respectively, towards appraising priority weight of different robot selection attributes and pertinent rating of candidate robots with respect to various attributes. The following linguistic terms set: {Very Low, VL; Low L; Medium Low, ML; Medium, M; Medium High, MH; High, H; Very High, VH} has been used to assign priority weight against different selection attributes. Similarly, the linguistic terms set: {Very Poor, VP; Poor, P; Medium Poor, MP; Fair, F; Medium Good, MG; Good, G; Very Good, VG} has been used to rate different alternatives with respect to different selection attributes. Assume that, a group of five decision-makers (DM1… DM5) has been involved in this decision making. DMs have been instructed to utilize aforementioned linguistic terms sets (Table 3.18-3.19) to express their expert judgment in relation to the robot selection decision making. Expert data (expressed in linguistic terms) in relation to attribute weight has been furnished in Table 3.20; and the ratings for qualitative attributes as given by the decision-makers have been furnished in Table 3.21.

Linguistic weights have been transformed into appropriate fuzzy numbers as prescribed in Table 3.18. Based on Eq. (3.29), aggregated fuzzy weights against individual selection attributes have been computed as shown in Table 3.20. Eq. (3.7) has been used to compute crisp weight and relative weight of various attributes as furnished in Table 3.20. The crisp weight set appears as {0.89, 0.93, 0.83, 0.87, 0.80 and 0.89} for attributes $C_1$… $C_6$, respectively. In this computation too, attribute $C_2$ corresponds to the highest weight and, therefore, treated as reference criterion/attribute. The relative weight set of different attributes $C_1$… $C_6$ have thus been computed as {0.95, 1.0, 0.90, 0.93, 0.86 and 0.95}, where $\sum_{i=1}^{m} W_{rc} = 5.59$.

Based on fuzzy aggregation rule (Eq. 3.28), aggregated fuzzy ratings against individual attributes (subjective attributes) have been computed as shown in Table 3.21. Table 3.22 represents the initial decision making matrix consisting of numeric data in relation to objective attributes and fuzzy data (ratings) for subjective attributes. As robot selection attributes consist of benefit as well as cost criteria both; the aforesaid initial fuzzy decision making matrix needs to be normalized. Eqs. (3.16) has been used to normalize the qualitative attributes ($C_4$, $C_5$, $C_6$) under fuzzy environment; while quantitative attributes ($C_1$, $C_2$, $C_3$) have been normalized by using the following equations (Eqs. 3.30-3.31).

$$r_{ij} = \frac{x_{ij}}{\underset{i}{Max}(x_{ij})},\ i = 1,2,...,m;\ j = 1,2,...,n. \quad \text{(For benefit criteria)} \tag{3.30}$$

$$r_{ij} = \frac{\underset{i}{Min}(x_{ij})}{x_{ij}},\ i = 1,2,...,m;\ j = 1,2,...,n. \quad \text{(For cost criteria)} \tag{3.31}$$

Here, $r_{ij}$ is the normalized value of $i^{th}$ alternative for $j^{th}$ criterion.

Load capacity ($C_2$) being a beneficial attribute, hence it has been normalized using Eq. (3.30); whereas, purchase cost ($C_1$) and repeatability ($C_3$) being non-beneficial (cost) attributes and hence these have been normalized using Eq. (3.31). The normalized fuzzy decision matrix has been provided in Table 3.23. Now the, crisp scores $m(\tilde{r}_{ij})$ against fuzzy normalized attribute (subjective attributes) ratings corresponding to different alternatives have been computed using Eq. (3.7) and shown in Table 3.24. Further the value of fuzzy distance measure between two alternatives (normalized fuzzy ratings for a particular criterion c), i.e., $d(\tilde{r}_{ic}, \tilde{r}_{jc})$ needs to be calculated using Eq. (3.13) to compute $\phi_c(\tilde{A}_i, \tilde{A}_j)$. Thus, the fuzzy distance measures corresponding to each pair of alternatives with respect to different qualitative criteria have been calculated from Table 3.23 and furnished in Table 3.25.

Now, evaluative difference between each pair of alternatives with respect to different criteria has been computed from Table 3.24 and shown in Table 3.26. For subjective attributes, evaluative difference has been computed through $\lfloor m(\tilde{r}_{ic}) - m(\tilde{r}_{jc}) \rfloor$; whereas, for objective attributes, it is computed based on $(r_{ic} - r_{jc})$ (refer to the original formulation of crisp-TODIM). By exploring the information from Table 3.24-3.26, the partial matrices of dominance (Table 3.27) has been developed using (Eq. 3.20) considering the value of $\theta$=1. A separate study has also been made for $\theta$=2.5 and the ranking orders thus obtained have been compared. The final matrices of dominance have then been computed (using Eq. 3.19) and furnished in Table 3.28. Finally, the global measures $(\xi_i)$ of candidate alternatives have been computed using (Eq. 3.21) and tabulated in Table 3.29. The ranking order of alternative robots appears as $A_3$>$A_1$>$A_2$ for both the values of $\theta$.

The ranking order obtained through F-TODIM has been compared to that of Fuzzy-TOPSIS. Utilizing the crisp data (rating) from Table 3.24, and the crisp weight from Table 3.20, the weighted normalized decision matrix has been developed and shown in Table 3.30. Next, the ideal and anti-ideal solutions ($A^*$, $A^-$, respectively) have been computed as furnished in Table 3.31. The distance of each alternative with respect to ideal as well as anti-ideal solution has been determined and furnished in Table 3.32. Finally, a closeness coefficient $(CC_i)$ has been determined for each of the alternatives followed by which preference order of the alternatives has been evaluated (Table 3.33). The ranking order of alternative robots that appears through exploration of fuzzy-TOPSIS is $A_3$>$A_1$>$A_2$. While comparing the results (ranking order of alternative robots) of F-TODIM to that of fuzzy-TOPSIS, it has been observed that for both the cases the appropriate alternative robot appears as $A_3$; whilst robot $A_2$ is the worst choice.

#### 3.1.1.4.3 Results on Exploration of Fuzzy Degree of Similarity into F-TODIM

In this part of work, the concept of fuzzy degree of similarity has been clubbed to the original formulation of F-TODIM. Considering *Case Illustration I*, exploring data from Table 3.6, degree of similarity between pairs of alternatives w.r.t. various criteria $S(\tilde{r}_{ic},\tilde{r}_{jc})$ have been evaluated (using Eq. 3.22) and furnished in Table 3.34. Considering the evaluative difference (on criteria values) for different alternative pairs, partial matrices of dominance have been constructed (using Eq. 3.27) as shown in Table 3.35. The final matrices of dominance for all alternative pairs have been furnished in Table 3.36. The global measures of alternatives have been tabulated in Table 3.37, for $\theta = 1$. The ranking order of alternative robots appear as: $A_1$>$A_2$>$A_3$>$A_4$. Now, the alternative ranking order by exploring the concept of fuzzy distance measure thus obtained (from Table 3.12) has been compared to that of obtained by exploring the concept of fuzzy similarity measure (Table 3.37). As compared with Table 3.12, it has been observed that the ranking order of preference of alternative robots appearing similar.

In continuation to *Case Illustration II*, utilizing the data in relation to normalized rating of various subjective attributes (Table 3.23), the measures of degree of similarity between alternative pairs with respect to different subjective attributes have been computed (by using Eq. 3.22) as furnished in Table 3.38. Now, utilizing the data from Table 3.24 (and by using relations Eq. (3.20) and Eq. (3.27), the partial matrices of dominance for the alternative pairs have been computed as shown in Table 3.39. The final matrices of dominance have been depicted in Table 3.40. The overall value (global measure) of the alternative robots have been computed next and shown in Table 3.41. The ranking order of alternative robots appears as $A_3>A_1>A_2$; which is same (Table 3.29) as obtained using the concept of fuzzy distance measure in the formulation of F-TODIM.

### 3.1.1.5 Concluding Remarks

Robot selection has always been viewed as an important decision making problem in industrial context. In recent marketplace, due to availability of wide variety of robotic systems offered by different robot manufacturers, appropriate robot selection has become a complex managerial decision making task. The decision making becomes much more complicated if the evaluation and selection is based on subjective selection attributes, apart from quantitative decision making data. Traditional MCDM tools can deal with objective data; whereas, difficulty is encountered if the problem is associated with purely subjective data or the combination of subjective as well as objective data set. Fuzzy set theory has been immensely popularized in decision making involving subjective data; since, fuzzy set has the ability to efficiently tackle inherent imprecision, ambiguity as well as vagueness arising from subjective human judgment. Therefore, traditional decision making tools and techniques have been integrated with fuzzy set theory to facilitate decision making. Most of the fuzzy based decision making tools do not consider risk attitude of the decision maker. However, TODIM approach has been formulated in such a manner that it reflects decision-makers' risk aversion attitude in case of gain; whereas, risk seeking attitude in case of loss. The TODIM method is basically an extension of Cumulative Prospect Theory (CPT) and represents the value function curve combining gain and loss. In this work traditional TODIM approach has been modified to work under fuzzy environment.

The attenuation factor $\theta$ in the TODIM method considers the risk aversion or propensity of the decision-maker. In this analysis, it has been observed that two different values for $\theta$ led essentially to the same ranking order of alternative robots which indicates the robustness of the results. The ranking of alternatives does not suffer any alteration by increasing the factor of attenuation of losses for $\theta = 1$ and $\theta = 2.5$.
In relation to robot selection, two case illustrations have been demonstrated in this work:

(i) Considering subjective data set and,

(ii) Data with a combination of subjective and objective data.

Application potential of fuzzy-based TODIM has been illustrated in this work. The ranking order of alternative robots as obtained through F-TODIM has been compared to that of fuzzy-TOPSIS; the most appropriate choice appears the same. The work also proposes exploration of the concept of fuzzy degree of similarity in the formulation of F-TODIM as means of effectively measuring dominance between two alternatives with respect to a particular criterion.

Table 3.1: Alternative Selection criteria

| Robot selection attributes | Notation |
|---|---|
| Man-machine interface | $C_1$ |
| Programming flexibility | $C_2$ |
| Vendor's service contract | $C_3$ |
| Purchase cost | $C_4$ |
| Load capacity | $C_5$ |
| Positioning accuracy | $C_6$ |

Table 3.2: 9 member linguistic terms and their corresponding triangular fuzzy numbers

[Source: Tsai et al., 2008]

| Linguistic terms for weight assignment | Linguistic terms for ratings | Triangular fuzzy numbers |
|---|---|---|
| Absolutely Unimportant (AU) | Absolutely Low, AL | (0.0, 0.1, 0.2) |
| Highly Unimportant (HU) | Very Low, VL | (0.1, 0.2, 0.3) |
| Unimportant (U) | Low, L | (0.2, 0.3, 0.4) |
| Rarely Important (RI) | Fairly Low, FL | (0.3, 0.4, 0.5) |
| Less Important (LI) | Medium, M | (0.4, 0.5, 0.6) |
| Fairly Important (FI) | Fairly High, FH | (0.5, 0.6, 0.7) |
| Important (I) | High, H | (0.6, 0.7, 0.8) |
| Very Important (VI) | Very High, VH | (0.7, 0.8, 0.9) |
| Absolutely Important (AI) | Absolutely High, AH | (0.8, 0.9, 1.0) |

Table 3.3: Importance weights of attributes assigned by the decision-makers

| Attribute, ($C_i$) | Subjective importance weights given by the Decision-Makers (Linguistic judgment) | | | | | | | | | | Aggregated fuzzy weights | Crisp weight | $W_{rc}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 | DM5 | DM6 | DM7 | DM8 | DM9 | DM10 | | | |
| $C_1$ | LI | FI | FI | I | FI | FI | I | I | I | I | (0.540,0.640,0.740) | 0.64 | 0.83 |
| $C_2$ | AI | AI | I | I | I | I | VI | I | VI | VI | (0.670,0.770,0.870) | 0.77 | 1.00 |
| $C_3$ | VI | VI | I | VI | I | I | VI | AI | I | I | (0.660,0.760,0.860) | 0.76 | 0.99 |
| $C_4$ | FI | FI | I | I | I | I | I | I | I | VI | (0.590,0.690,0.790) | 0.69 | 0.90 |
| $C_5$ | I | I | I | VI | I | I | I | I | I | I | (0.610,0.710,0.810) | 0.71 | 0.92 |
| $C_6$ | I | I | I | I | VI | VI | I | I | I | I | (0.620,0.720,0.820) | 0.72 | 0.94 |

Table 3.4: Rating of attributes assigned by the decision-makers

| Attributes ($C_i$) | Alternative | Subjective performance rating (in linguistic term) given by the Decision-Makers | | | | | | | | | | Aggregated fuzzy rating $\left(\tilde{x}_{ij}\right)$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | DM1 | DM2 | DM3 | DM4 | DM5 | DM6 | DM7 | DM8 | DM9 | DM10 | |
| $C_1$ | $A_1$ | H | H | FH | H | FH | M | FH | M | FH | FH | (0.510,0.610,0.710) |
| | $A_2$ | VH | VH | AH | VH | VH | AH | AH | VH | VH | VH | (0.730,0.830,0.930) |
| | $A_3$ | VH | VH | VH | VH | VH | H | VH | VH | H | H | (0.670,0.770,0.870) |
| | $A_4$ | H | H | FH | H | FH | FH | FH | FH | FH | FH | (0.530,0.630,0.730) |
| $C_2$ | $A_1$ | M | FH | M | FH | FH | H | H | VH | H | H | (0.540,0.640,0.740) |
| | $A_2$ | M | M | M | M | M | M | M | M | FL | M | (0.390,0.490,0.590) |
| | $A_3$ | FL | FL | M | M | M | H | VH | H | VH | VH | (0.510,0.610,0.710) |
| | $A_4$ | H | H | H | VH | VH | AH | VH | VH | VH | VH | (0.680,0.780,0.880) |
| $C_3$ | $A_1$ | M | M | M | M | FH | H | H | H | H | H | (0.510,0.610,0.710) |
| | $A_2$ | VH | VH | H | FH | FH | FH | H | H | H | H | (0.590,0.690,0.790) |
| | $A_3$ | M | M | M | FL | FL | AH | AH | VH | VH | VH | (0.550,0.650,0.750) |
| | $A_4$ | L | L | FL | L | L | H | VH | VH | H | H | (0.430,0.530,0.630) |
| $C_4$ | $A_1$ | FH | FH | FH | FH | FH | FH | FH | H | FH | FH | (0.510,0.610,0.710) |
| | $A_2$ | H | H | H | FH | H | H | H | VH | H | H | (0.600,0.700,0.800) |
| | $A_3$ | VH | H | VH | VH | VH | M | M | M | FL | M | (0.530,0.630,0.730) |
| | $A_4$ | VH | VH | VH | VH | VH | H | VH | H | VH | VH | (0.680,0.780,0.880) |
| $C_5$ | $A_1$ | H | H | FH | H | FH | AH | VH | AH | VH | VH | (0.650,0.750,0.850) |
| | $A_2$ | M | FH | M | FH | FH | H | H | FH | H | H | (0.520,0.620,0.720) |
| | $A_3$ | M | M | FH | M | M | FH | H | H | H | H | (0.500,0.600,0.700) |
| | $A_4$ | FL | FL | M | M | M | AH | AH | AH | VH | VH | (0.560,0.660,0.760) |
| $C_6$ | $A_1$ | H | H | FH | VH | VH | FH | FH | FH | FH | FH | (0.560,0.660,0.760) |
| | $A_2$ | M | M | M | M | FH | H | H | VH | H | H | (0.520,0.620,0.720) |
| | $A_3$ | VH | VH | H | FH | FH | M | M | M | FL | M | (0.490,0.590,0.690) |
| | $A_4$ | M | M | M | FL | FL | H | VH | H | VH | VH | (0.510,0.610,0.710) |

Table 3.5: Initial fuzzy decision making matrix

| $A_j$ | $\tilde{x}_{ij}$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$ | (0.51, 0.61, 0.71) | (0.54, 0.64, 0.74) | (0.51, 0.61, 0.71) | (0.51, 0.61, 0.71) | (0.65, 0.75, 0.85) | (0.56, 0.66, 0.76) |
| $A_2$ | (0.73, 0.83, 0.93) | (0.39, 0.49, 0.59) | (0.59, 0.69, 0.79) | (0.60, 0.70, 0.80) | (0.52, 0.62, 0.72) | (0.52, 0.62, 0.72) |
| $A_3$ | (0.67, 0.77, 0.87) | (0.51, 0.61, 0.71) | (0.55, 0.65, 0.75) | (0.53, 0.63, 0.73) | (0.50, 0.60, 0.70) | (0.49, 0.59, 0.69) |
| $A_4$ | (0.53, 0.63, 0.73) | (0.68, 0.78, 0.88) | (0.43, 0.53, 0.63) | (0.68, 0.78, 0.88) | (0.56, 0.66, 0.76) | (0.51, 0.61, 0.71) |

Table 3.6: Normalized decision making matrix

| Aj | $\tilde{r}_{ij}$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$ | (0.548, 0.656, 0.763) | (0.614, 0.727, 0.841) | (0.646, 0.772, 0.899) | (0.718, 0.836, 1.00) | (0.765, 0.882, 1.00) | (0.737, 0.868, 1.00) |
| $A_2$ | (0.785, 0.892, 1.00) | (0.443, 0.557, 0.670) | (0.747, 0.873, 1.00) | (0.638, 0.729, 0.850) | (0.612, 0.729, 0.847) | (0.684, 0.816, 0.947) |
| $A_3$ | 0.720, 0.828, 0.935) | (0.580, 0.693, 0.807) | (0.696, 0.823, 0.949) | (0.699, 0.810, 0.962) | (0.588, 0.706, 0.824) | (0.645, 0.776, 0.908) |
| $A_4$ | (0.570, 0.677, 0.785) | (0.773, 0.886, 1.00) | (0.544, 0.671, 0.797) | (0.580, 0.654, 0.750) | (0.659, 0.776, 0.894) | (0.671, 0.803, 0.934) |

Table 3.7: Crisp score against normalized fuzzy rating of alternatives w.r.t. different attributes

| $A_i$ | $m(\tilde{r}_{ij})$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$ | 0.656 | 0.727 | 0.772 | 0.851 | 0.882 | 0.868 |
| $A_2$ | 0.892 | 0.557 | 0.873 | 0.739 | 0.729 | 0.816 |
| $A_3$ | 0.828 | 0.693 | 0.823 | 0.823 | 0.706 | 0.776 |
| $A_4$ | 0.677 | 0.886 | 0.671 | 0.661 | 0.776 | 0.803 |

Table 3.8: Fuzzy distance measure for each pair of alternatives w.r.t. different criteria

| Alternative pairs | $d(\tilde{r}_{ic}, \tilde{r}_{jc})$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $(A_1, A_2)$ | 0.237 | 0.170 | 0.101 | 0.116 | 0.153 | 0.053 |
| $(A_1, A_3)$ | 0.172 | 0.034 | 0.051 | 0.029 | 0.176 | 0.092 |
| $(A_1, A_4)$ | 0.022 | 0.159 | 0.101 | 0.196 | 0.106 | 0.066 |
| $(A_2, A_1)$ | 0.237 | 0.170 | 0.101 | 0.116 | 0.153 | 0.053 |
| $(A_2, A_3)$ | 0.065 | 0.136 | 0.051 | 0.087 | 0.024 | 0.039 |
| $(A_2, A_4)$ | 0.215 | 0.330 | 0.203 | 0.079 | 0.047 | 0.013 |
| $(A_3, A_1)$ | 0.172 | 0.034 | 0.051 | 0.029 | 0.176 | 0.092 |
| $(A_3, A_2)$ | 0.065 | 0.136 | 0.051 | 0.087 | 0.024 | 0.039 |
| $(A_3, A_4)$ | 0.151 | 0.193 | 0.152 | 0.167 | 0.071 | 0.026 |
| $(A_4, A_1)$ | 0.022 | 0.159 | 0.101 | 0.196 | 0.106 | 0.066 |
| $(A_4, A_2)$ | 0.329 | 0.330 | 0.203 | 0.079 | 0.047 | 0.013 |
| $(A_4, A_3)$ | 0.151 | 0.193 | 0.152 | 0.167 | 0.071 | 0.026 |

Table 3.9: Computation of evaluative differences $\left[m\left(\tilde{r}_{ic}\right)-m\left(\tilde{r}_{jc}\right)\right]$

| Pair | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| ($A_1$, $A_2$) | -0.237 | 0.170 | -0.101 | 0.113 | 0.153 | 0.053 |
| ($A_1$, $A_3$) | -0.172 | 0.034 | -0.051 | 0.028 | 0.176 | 0.092 |
| ($A_1$, $A_4$) | -0.022 | -0.159 | 0.101 | 0.190 | 0.106 | 0.066 |
| ($A_2$, $A_1$) | 0.237 | -0.170 | 0.101 | -0.113 | -0.153 | -0.053 |
| ($A_2$, $A_3$) | 0.065 | -0.136 | 0.051 | -0.085 | 0.024 | 0.039 |
| ($A_2$, $A_4$) | 0.215 | -0.330 | 0.203 | 0.078 | -0.047 | 0.013 |
| ($A_3$, $A_1$) | 0.172 | -0.034 | 0.051 | -0.028 | -0.176 | -0.092 |
| ($A_3$, $A_2$) | -0.065 | 0.136 | -0.051 | 0.085 | -0.024 | -0.039 |
| ($A_3$, $A_4$) | 0.151 | -0.193 | 0.152 | 0.162 | -0.071 | -0.026 |
| ($A_4$, $A_1$) | 0.022 | 0.159 | -0.101 | -0.190 | -0.106 | -0.066 |
| ($A_4$, $A_2$) | -0.215 | 0.330 | -0.203 | -0.078 | 0.047 | -0.013 |
| ($A_4$, $A_3$) | -0.151 | 0.193 | -0.152 | -0.162 | 0.071 | 0.026 |

Table 3.10: Partial matrices of dominance $(\theta = 1)$

| Pair | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| ($A_1$, $A_2$) | -1.261 | 0.175 | -0.755 | 0.137 | 0.159 | 0.094 |
| ($A_1$, $A_3$) | -1.075 | 0.078 | -0.534 | 0.068 | 0.171 | 0.125 |
| ($A_1$, $A_4$) | -0.380 | -0.942 | 0.134 | 0.178 | 0.132 | 0.105 |
| ($A_2$, $A_1$) | 0.188 | -0.975 | 0.134 | -0.849 | -0.963 | -0.559 |
| ($A_2$, $A_3$) | 0.098 | -0.872 | 0.095 | -0.736 | 0.062 | 0.082 |
| ($A_2$, $A_4$) | 0.179 | -1.356 | 0.190 | 0.113 | -0.534 | 0.047 |
| ($A_3$, $A_1$) | 0.160 | -0.436 | 0.095 | -0.424 | -1.035 | -0.739 |
| ($A_3$, $A_2$) | -0.659 | 0.156 | -0.534 | 0.119 | -0.378 | -0.484 |
| ($A_3$, $A_4$) | 0.150 | -1.038 | 0.164 | 0.164 | -0.654 | -0.395 |
| ($A_4$, $A_1$) | 0.057 | 0.169 | -0.755 | -1.102 | -0.801 | -0.625 |
| ($A_4$, $A_2$) | -1.486 | 0.243 | -1.068 | -0.702 | 0.088 | -0.279 |
| ($A_4$, $A_3$) | -1.006 | 0.186 | -0.925 | -1.017 | 0.108 | 0.067 |

Table 3.11: Final matrices of dominance for all the pairs of alternatives

| Robot | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0.00 | -1.45 | -1.17 | -0.77 |
| $A_2$ | -3.02 | 0.00 | -1.27 | -1.36 |
| $A_3$ | -2.38 | -1.78 | 0.00 | -1.61 |
| $A_4$ | -3.06 | -3.20 | -2.59 | 0.00 |

Table 3.12: Overall value (global measures) of alternatives

| Robot | $\sum_{j=1}^{n}\delta(A_i, A_j)$ (for θ= 1) | $\xi_i$ | Ranking order | $\sum_{j=1}^{n}\delta(A_i, A_j)$ (for θ= 2.5) | $\xi_i$ | Ranking order |
|---|---|---|---|---|---|---|
| $A_1$ | -3.39 | 1.00 | 1 | -0.46 | 1.00 | 1 |
| $A_2$ | -5.65 | 0.59 | 2 | -1.56 | 0.57 | 2 |
| $A_3$ | -5.77 | 0.56 | 3 | -1.71 | 0.51 | 3 |
| $A_4$ | -8.85 | 0.00 | 4 | -2.99 | 0.00 | 4 |

Table 3.13: Weighted fuzzy decision matrix

| $A_i$ | Weighted ratings | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$ | (0.275,0.390,0.525) | (0.362,0.493,0.644) | (0.337,0.464,0.611) | (0.301,0.421,0.561) | (0.397,0.533,0.689) | (0.347,0.475,0.623) |
| $A_2$ | (0.394,0.531,0.688) | (0.261,0.377,0.513) | (0.389,0.524,0.679) | (0.354,0.483,0.632) | (0.317,0.440,0.583) | (0.322,0.446,0.590) |
| $A_3$ | (0.362,0.493,0.644) | (0.342,0.470,0.618) | (0.363,0.494,0.645) | (0.372,0.435,0.577) | (0.305,0.426,0.567) | (0.304,0.374,0.566) |
| $A_4$ | (0.286,0.403,0.540) | (0.456,0.601,0.766) | (0.284,0.403,0.542) | (0.401,0.538,0.695) | (0.342,0.469,0.616) | (0.316,0.439,0.582) |

Table 3.14: Ideal and anti-ideal solutions

| Ideal solution A* | | | | | |
|---|---|---|---|---|---|
| C1 | C2 | C3 | C4 | C5 | C6 |
| (1,1,1) | (1,1,1) | (1,1,1) | (0,0,0) | (1,1,1) | (1,1,1) |
| Negative ideal solution A- | | | | | |
| (0,0,0) | (0,0,0) | (0,0,0) | (1,1,1) | (0,0,0) | (0,0,0) |

Table 3.15: Computed distance measure individual alternative w.r.t. ideal ($A^*$) as well as anti-ideal ($A^-$) solution

| $A_i$ | Computed distance measure from positive ideal solution $A^*$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$ | 0.608 | 0.511 | 0.539 | 0.438 | 0.474 | 0.528 |
| $A_2$ | 0.475 | 0.621 | 0.481 | 0.500 | 0.561 | 0.555 |
| $A_3$ | 0.511 | 0.533 | 0.510 | 0.452 | 0.574 | 0.576 |
| $A_4$ | 0.596 | 0.411 | 0.597 | 0.555 | 0.534 | 0.562 |
| Computed distance measure from anti-ideal solution $A^-$ | | | | | | |
| $A_1$ | 0.408 | 0.510 | 0.481 | 0.579 | 0.549 | 0.492 |
| $A_2$ | 0.548 | 0.396 | 0.541 | 0.520 | 0.458 | 0.464 |
| $A_3$ | 0.510 | 0.487 | 0.511 | 0.566 | 0.443 | 0.442 |
| $A_4$ | 0.421 | 0.617 | 0.421 | 0.468 | 0.486 | 0.457 |

Table 3.16: Computed preference order of candidate alternatives

| $A_i$ | $d_i^*$ | $d_i^-$ | $CC_i$ | Ranking order |
|---|---|---|---|---|
| $A_1$ | 3.098 | 3.020 | 0.494 | 1 |
| $A_2$ | 3.194 | 2.927 | 0.478 | 3 |
| $A_3$ | 3.156 | 2.960 | 0.484 | 2 |
| $A_4$ | 3.255 | 2.869 | 0.469 | 4 |

Table 3.17: Robot selection attributes (Combination of subjective and objective data) [Rao and Padmanabhan, 2006]

| Alternative | Purchase Cost ($x1000), $C_1$ | Load Capacity (kg), $C_2$ | Repeatability (mm), $C_3$ | Man-machine interface, $C_4$ | Programming flexibility, $C_5$ | Vendors service contract, $C_6$ |
|---|---|---|---|---|---|---|
| $A_1$ | 70 | 45 | 0.16 | To be evaluated by DMs | To be evaluated by DMs | To be evaluated by DMs |
| $A_2$ | 68 | 45 | 0.17 | To be evaluated by DMs | To be evaluated by DMs | To be evaluated by DMs |
| $A_3$ | 73 | 50 | 0.12 | To be evaluated by DMs | To be evaluated by DMs | To be evaluated by DMs |

Table 3.18: Linguistic variables for the importance weight of each criterion (Chen, 2000)

| Linguistic variables | Fuzzy numbers |
|---|---|
| Very Low (VL) | (0, 0, 0.1) |
| Low (L) | (0, 0.1, 0.3) |
| Medium Low (ML) | (0.1, 0.3, 0.5) |
| Medium (M) | (0.3, 0.5, 0.7) |
| Medium High (MH) | (0.5, 0.7, 0.9) |
| High (H) | (0.7, 0.9, 1.0) |
| Very High (VH) | (0.9, 1.0, 1.0) |

Table 3.19: Linguistic variables for the ratings of each (subjective) criterion (Chen, 2000)

| Linguistic variables | Fuzzy numbers |
|---|---|
| Very Poor (VP) | (0, 0, 1) |
| Poor (P) | (0, 1, 3) |
| Medium Poor (MP) | (1, 3, 5) |
| Fair (F) | (3, 5, 7) |
| Medium Good (MG) | (5, 7, 9) |
| Good (G) | (7, 9, 10) |
| Very Good (VG) | (9, 10, 10) |

Table 3.20: Importance weights of attributes assigned by the decision-makers

| Attribute, ($C_i$) | Subjective importance weights given by the Decision-Makers (Linguistic judgment) | | | | | Aggregated fuzzy weights | Crisp weight | $w_{rc}$ |
|---|---|---|---|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 | DM5 | | | |
| $C_1$ | H | H | H | H | VH | (0.74, 0.92, 1.0) | 0.89 | 0.95 |
| $C_2$ | H | VH | VH | VH | H | (0.82, 0.96, 1.0) | 0.93 | 1.00 |
| $C_3$ | MH | H | H | H | H | (0.66, 0.86, 0.98) | 0.83 | 0.90 |
| $C_4$ | H | H | H | H | H | (0.70, 0.90, 1.0) | 0.87 | 0.93 |
| $C_5$ | MH | MH | H | H | H | (0.62, 0.82, 0.96) | 0.80 | 0.86 |
| $C_6$ | H | VH | H | H | H | (0.74, 0.92, 1.0) | 0.89 | 0.95 |

Table 3.21: Priority rating of attributes assigned by the decision-makers

| Attributes ($C_i$) | Alternative | Subjective performance rating (in linguistic term) given by the Decision-Makers | | | | | Aggregated fuzzy rating |
|---|---|---|---|---|---|---|---|
| | | DM1 | DM2 | DM3 | DM4 | DM5 | |
| $C_4$ | $A_1$ | VG | G | G | G | G | (7.4, 9.2, 10) |
| | $A_2$ | P | MP | MP | MP | MP | (0.8, 206, 4.6) |
| | $A_3$ | G | G | G | G | G | (7.0, 9.0, 10) |
| $C_5$ | $A_1$ | G | G | G | G | G | (7.0, 9.0, 10) |
| | $A_2$ | F | MP | F | F | F | (2.6, 4.6, 6.6) |
| | $A_3$ | G | MG | MG | G | G | (6.2, 8.2, 9.6) |
| $C_6$ | $A_1$ | MG | MG | G | G | G | (6.2, 8.2, 9.6) |
| | $A_2$ | MG | G | MG | G | G | (6.2, 8.2, 9.6) |
| | $A_3$ | G | G | VG | VG | G | (7.8, 9.4, 10) |

Table 3.22: Initial decision making matrix

| Aj | $C_1$ ($x1000) | $C_2$ (kg) | $C_3$ (mm) | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| A1 | 73 | 45 | 0.16 | (7.4, 9.2, 10) | (7, 9, 10) | (6.2, 8.2, 9.6) |
| A2 | 68 | 45 | 0.17 | (0.8, 206, 4.6) | (2.6, 4.6, 6.6) | (6.2, 8.2, 9.6) |
| A3 | 73 | 50 | 0.12 | (7, 9, 10) | (6.2, 8.2, 9.6) | (7.8, 9.4, 10) |

Table 3.23: Normalized decision making matrix

| Aj | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.97 | 0.90 | 0.75 | (0.74, 0.92, 1.0) | (0.70, 0.90, 1.0) | (0.62, 0.82, 0.96) |
| $A_2$ | 1.00 | 0.90 | 0.71 | (0.08, 0.26, 0.46) | (0.26, 0.46, 0.66) | (0.62, 0.82, 0.96) |
| $A_3$ | 0.93 | 1.00 | 1.00 | (0.70, 0.90, 1.0) | (0.62, 0.82, 0.96) | (0.78, 0.94, 1.0) |

Table 3.24: Crisp score against normalized rating of alternatives w.r.t. different attributes

| $A_i$ | $r_{ij}$ | | | $m(\tilde{r}_{ij})$ | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$ | 0.97 | 0.90 | 0.75 | 0.89 | 0.87 | 0.80 |
| $A_2$ | 1.00 | 0.90 | 0.71 | 0.27 | 0.46 | 0.80 |
| $A_3$ | 0.93 | 1.00 | 1.00 | 0.87 | 0.80 | 0.91 |

Table 3.25: Fuzzy distance measure for each pair of alternatives with respect to different qualitative criteria

| Alternative pairs | $d(\tilde{r}_{ic}, \tilde{r}_{jc})$ | | |
|---|---|---|---|
| | $C_4$ | $C_5$ | $C_6$ |
| $A_1$, $A_2$ | 0.116 | 0.153 | 0.053 |
| $A_1$, $A_3$ | 0.029 | 0.176 | 0.092 |
| $A_2$, $A_1$ | 0.116 | 0.153 | 0.053 |
| $A_2$, $A_3$ | 0.087 | 0.024 | 0.039 |
| $A_3$, $A_1$ | 0.029 | 0.176 | 0.092 |
| $A_3$, $A_2$ | 0.087 | 0.024 | 0.039 |

Table 3.26: Computation of evaluative differences

| Pair | $(r_{ic} - r_{jc})$ | | | $[m(\tilde{r}_{ic}) - m(\tilde{r}_{jc})]$ | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$, $A_2$ | -0.03 | 0.00 | 0.04 | 0.62 | 0.41 | 0.00 |
| $A_1$, $A_3$ | 0.04 | -0.10 | -0.25 | 0.02 | 0.07 | -0.11 |
| $A_2$, $A_1$ | 0.03 | 0.00 | -0.04 | -0.62 | -0.41 | 0.00 |
| $A_2$, $A_3$ | 0.07 | -0.10 | -0.29 | -0.60 | -0.34 | -0.11 |
| $A_3$, $A_1$ | -0.04 | 0.10 | 0.25 | -0.02 | -0.07 | 0.11 |
| $A_3$, $A_2$ | -0.07 | 0.10 | 0.29 | 0.60 | 0.34 | 0.11 |

Table 3.27: Partial matrices of dominance $(\theta = 1)$

| Pair | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| $A_1$, $A_2$ | -0.41 | 0.00 | 0.08 | 0.32 | 0.25 | 0.00 |
| $A_1$, $A_3$ | 0.08 | -0.75 | -1.25 | 0.06 | 0.10 | -0.79 |
| $A_2$, $A_1$ | 0.07 | 0.00 | -0.52 | -1.93 | -1.63 | 0.00 |
| $A_2$, $A_3$ | 0.11 | -0.75 | -1.35 | -1.90 | -1.49 | -0.79 |
| $A_3$, $A_1$ | -0.48 | 0.13 | 0.20 | -0.35 | -0.66 | 0.13 |
| $A_3$, $A_2$ | -0.63 | 0.13 | 0.22 | 0.32 | 0.23 | 0.13 |

Table 3.28: Final matrices of dominance

| Robot | A1 | A2 | A3 |
|---|---|---|---|
| A1 | 0 | 0.25 | -2.54 |
| A2 | -4.01 | 0 | -6.17 |
| A3 | -1.02 | 0.4 | 0 |

Table 3.29: Overall value (global measures) of alternatives

| Robot | $\sum_{j=1}^{n}\delta(A_i, A_j)$ (for θ= 1) | $\xi$ | Ranking order | $\sum_{j=1}^{n}\delta(A_i, A_j)$ (for θ= 2.5) | $\xi$ | Ranking order |
|---|---|---|---|---|---|---|
| $A_1$ | -2.29 | 0.83 | 2 | -0.38 | 0.78 | 2 |
| $A_2$ | -10.18 | 0.00 | 3 | -3.96 | 0.00 | 3 |
| $A_3$ | -0.62 | 1.00 | 1 | 0.65 | 1.00 | 1 |

Table 3.30: Weighted normalized crisp decision matrix

| Aj | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.86 | 0.84 | 0.62 | 0.77 | 0.69 | 0.71 |
| $A_2$ | 0.89 | 0.84 | 0.59 | 0.23 | 0.37 | 0.71 |
| $A_3$ | 0.83 | 0.93 | 0.83 | 0.75 | 0.64 | 0.81 |

Table 3.31: Ideal and anti-ideal solutions

| Ideal solution $A^*$ | | | | | |
|---|---|---|---|---|---|
| $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| 0.89 | 0.93 | 0.83 | 0.77 | 0.69 | 0.81 |
| Negative ideal solution $A^-$ | | | | | |
| 0.83 | 0.84 | 0.59 | 0.23 | 0.37 | 0.71 |

Table 3.32: Computed distance measure of individual alternative w.r.t. ideal ($A^*$) as well as anti-ideal ($A^-$) solution

| $A_i$ | Computed distance measure from positive ideal solution $A^*$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$ | 0.001 | 0.009 | 0.043 | 0.000 | 0.000 | 0.010 |
| $A_2$ | 0.000 | 0.009 | 0.058 | 0.289 | 0.104 | 0.010 |
| $A_3$ | 0.004 | 0.000 | 0.000 | 0.000 | 0.002 | 0.000 |
| Computed distance measure from anti-ideal solution $A^-$ | | | | | | |
| $A_1$ | 0.001 | 0.000 | 0.001 | 0.293 | 0.105 | 0.000 |
| $A_2$ | 0.004 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $A_3$ | 0.000 | 0.008 | 0.058 | 0.275 | 0.073 | 0.009 |

Table 3.33: Computed preference order of candidate alternatives

| $A_i$ | $d_i^*$ | $d_i^-$ | $CC_i$ | Ranking order |
|---|---|---|---|---|
| $A_1$ | 0.25 | 0.63 | 0.72 | 2 |
| $A_2$ | 0.69 | 0.06 | 0.08 | 3 |
| $A_3$ | 0.08 | 0.65 | 0.89 | 1 |

Table 3.34: Degree of similarity for each pair of alternatives w.r.t. different criteria

| Alternative pairs | $S(\tilde{r}_{ic}, \tilde{r}_{jc})$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$,$A_2$ | 0.763 | 0.830 | 0.899 | 0.868 | 0.847 | 0.947 |
| $A_1$, $A_3$ | 0.828 | 0.966 | 0.949 | 0.966 | 0.824 | 0.908 |
| $A_1$, $A_4$ | 0.978 | 0.841 | 0.899 | 0.781 | 0.894 | 0.934 |
| $A_2$, $A_1$ | 0.763 | 0.830 | 0.899 | 0.868 | 0.847 | 0.947 |
| $A_2$, $A_3$ | 0.935 | 0.864 | 0.949 | 0.900 | 0.976 | 0.961 |
| $A_2$, $A_4$ | 0.785 | 0.670 | 0.797 | 0.910 | 0.953 | 0.987 |
| $A_3$, $A_1$ | 0.828 | 0.966 | 0.949 | 0.966 | 0.824 | 0.908 |
| $A_3$, $A_2$ | 0.935 | 0.864 | 0.949 | 0.900 | 0.976 | 0.961 |
| $A_3$, $A_4$ | 0.849 | 0.807 | 0.848 | 0.813 | 0.929 | 0.974 |
| $A_4$, $A_1$ | 0.978 | 0.841 | 0.899 | 0.781 | 0.894 | 0.934 |
| $A_4$, $A_2$ | 0.785 | 0.670 | 0.797 | 0.910 | 0.953 | 0.987 |
| $A_4$, $A_3$ | 0.849 | 0.807 | 0.848 | 0.813 | 0.929 | 0.974 |

Table 3.35: Partial matrices of dominance $(\theta = 1)$

| Pair | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| $A_1$, $A_2$ | -1.286 | 0.175 | -0.755 | 0.146 | 0.159 | 0.094 |
| $A_1$, $A_3$ | -1.096 | 0.078 | -0.534 | 0.074 | 0.171 | 0.125 |
| $A_1$, $A_4$ | -0.388 | -0.942 | 0.134 | 0.188 | 0.132 | 0.105 |
| $A_2$, $A_1$ | 0.188 | -0.975 | 0.134 | -0.906 | -0.963 | -0.559 |
| $A_2$, $A_3$ | 0.098 | -0.872 | 0.095 | -0.786 | 0.062 | 0.082 |
| $A_2$, $A_4$ | 0.179 | -1.356 | 0.190 | 0.120 | -0.534 | 0.047 |
| $A_3$, $A_1$ | 0.160 | -0.436 | 0.095 | -0.458 | -1.035 | -0.739 |
| $A_3$, $A_2$ | -0.659 | 0.156 | -0.534 | 0.127 | -0.378 | -0.484 |
| $A_3$, $A_4$ | 0.150 | -1.038 | 0.164 | 0.174 | -0.654 | -0.395 |
| $A_4$, $A_1$ | 0.057 | 0.169 | -0.755 | -1.165 | -0.801 | -0.625 |
| $A_4$, $A_2$ | -2.342 | 0.243 | -1.068 | -0.747 | 0.088 | -0.279 |
| $A_4$, $A_3$ | -2.436 | 0.186 | -0.925 | -1.077 | 0.108 | 0.067 |

Table 3.36: Final matrices of dominance for all the pairs of alternatives

| Robot | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0.00 | -1.47 | -1.18 | -0.77 |
| $A_2$ | -3.08 | 0.00 | -1.32 | -1.35 |
| $A_3$ | -2.41 | -1.77 | 0.00 | -1.60 |
| $A_4$ | -3.12 | -4.11 | -4.08 | 0.00 |

Table 3.37: Overall value (global measures) of alternatives

| Robot | $\sum_{j=1}^{n}\delta(A_i, A_j)$ $\theta = 1$ | $\xi_i$ | Ranking order |
|---|---|---|---|
| $A_1$ | -3.42 | 1.00 | 1 |
| $A_2$ | -5.75 | 0.70 | 2 |
| $A_3$ | -5.78 | 0.70 | 3 |
| $A_4$ | -11.31 | 0.00 | 4 |

Table 3.38: Degree of similarity between alternative pairs with respect to various subjective criteria

| Pairs | $S(\tilde{r}_{ic}, \tilde{r}_{jc})$ | | |
|---|---|---|---|
| | $C_4$ | $C_5$ | $C_6$ |
| $A_1$, $A_2$ | 0.36 | 0.57 | 1.00 |
| $A_1$, $A_3$ | 0.95 | 0.92 | 0.85 |
| $A_2$, $A_1$ | 0.36 | 0.57 | 1.00 |
| $A_2$, $A_3$ | 0.38 | 0.64 | 0.85 |
| $A_3$, $A_1$ | 0.95 | 0.92 | 0.85 |
| $A_3$, $A_2$ | 0.38 | 0.64 | 0.85 |

Table 3.39: Partial matrices of dominance $(\theta = 1)$

| Pairs | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| $A_1$, $A_2$ | -0.41 | 0.00 | 0.08 | 0.33 | 0.26 | 0.00 |
| $A_1$, $A_3$ | 0.08 | -0.75 | -1.25 | 0.09 | 0.11 | -0.93 |
| $A_2$, $A_1$ | 0.07 | 0.00 | -0.52 | -1.97 | -1.68 | 0.00 |
| $A_2$, $A_3$ | 0.11 | -0.75 | -1.35 | -1.93 | -1.53 | -0.93 |
| $A_3$, $A_1$ | -0.48 | 0.13 | 0.20 | -0.55 | -0.72 | 0.16 |
| $A_3$, $A_2$ | -0.63 | 0.13 | 0.22 | 0.32 | 0.24 | 0.16 |

Table 3.40: Final matrices of dominance

| $A_i$ | $A_1$ | $A_2$ | $A_3$ |
|---|---|---|---|
| $A_1$ | 0.0 | 0.26 | -2.64 |
| $A_2$ | -4.1 | 0.0 | -6.37 |
| $A_3$ | -1.26 | 0.43 | 0.0 |

Table 3.41: Overall value (global measures) of alternatives

| Robot | $\sum_{j=1}^{n} \delta(A_i, A_j)$ $\theta = 1$ | $\xi$ | Rank |
|---|---|---|---|
| $A_1$ | -2.38 | 0.84 | 2 |
| $A_2$ | -10.47 | 0.00 | 3 |
| $A_3$ | -0.83 | 1.00 | 1 |

# 3.1.2 Extension of TODIM Combined with Grey Numbers: An Integrated Decision Making Module towards Selection of Industrial Robot

## 3.1.2.1 Coverage

In this part of work traditional TODIM approach has been extended in conjugation with grey set theory to facilitate robot selection problem from the perspective of decision making. As subjective criteria cannot be assessed by crisp numbers; the decision making relies on subjective judgment of the Decision-Makers (DMs). Since subjective human judgment bears ambiguity and vagueness in the decision making; application of grey numbers set theory may be proved fruitful in this context. Application of grey numbers set theory can take care of uncertainty, imprecision and incompleteness arising from subjective human judgment; it provides a grey-based mathematical foundation to support logical decision making Owing to the advantages of grey numbers set theory in tackling subjectivity in decision making; the crisp-TODIM needs to be extended by integrating with grey numbers set theory in order to facilitate decision making consisting of subjective data. Hence, the unified objective of the present work is to propose a grey based TODIM approach in the context of decision making.

Application potential of grey based decision support systems (grey-TOPSIS, Grey Relation analysis (GRA), grey-MOORA) have been highlighted in available literature resource. However, the shortcoming of these approaches is that they do not consider decision-makers' risk attitude whilst decision making. TODIM method is derived from the philosophy of Cumulative Prospect Theory (CPT) which considers risk averting attitude of the decision-maker in case of gain and risk seeking attitude in case of loss, while comparing dominance between two alternatives with respect to a particular criterion. Hence, this work contributes a mathematical foundation of TODIM coupled with grey numbers set theory for logical decision making. Application potential of grey-TODIM has been demonstrated through a case empirical robot selection problem. Result obtained thereof, has also been compared to that of existing grey based decision support systems available in literature.

### 3.1.2.2 Background and Problem Statement

Grey theory was earlier proposed by (Ju-Long Deng, 1982) to accord with partially known and partially unknown information. In grey theory, a system whose information is completely known is appeared as a 'white' system and a system whose information is completely unknown is appeared as a 'black' system; however, a system whose information is partly known or partly unknown is entitled as a 'grey' system. Indeterminate subjective judgment given by the decision-makers is barely possible to evaluate in terms of precise mathematical values; thus, exploration of grey theory may be proved fruitful to tackle ambiguity as well as vagueness of subjective human judgment. In fact, incomplete information is the basic characteristic of the problems considered in grey systems theory (Lin et al., 2004). Grey system theory (Deng, 1982) is one that encounters uncertain information circumstances and uses grey numbers to define this kind of ambiguity (multi-possibility) as well as vagueness. This theory was widely adopted in many fields, such as financial institutions, advertising agencies, management, etc. (Kung and Wen, 2007). The advantage of grey theory over fuzzy sets theory is that grey theory can deal flexibly with the fuzziness situation (Li et al. 2007b). Grey numbers theory was presented by several authors in amalgamation with traditional MCDM techniques resulting grey-TOPSIS, grey-VIKOR, grey-MOORA, grey-PROMETHEE etc.

Deng (1982) proposed a block theorem of the grey channel with some properties of grey parameters like grey matrices along with the grey systems; the author successfully anticipated a grey decision making method to determine the irrigation strategies. Further, a grey based decision making approach was effectively applied to the supplier selection problem by (Li et al., 2007b). Hsu and Wen (2000) recommended the grey theory as one of the feasible mathematical device capable of forecasting airline traffic with minimum data. The authors further emphasized that grey theory could effectively resolve problems comprising uncertainty and indetermination. Chen and Tzeng (2004) used fuzzy-AHP to determine the priority weights of subjective attributes and combined grey relation with TOPSIS concepts for selecting an expatriate host country.

Kuo et al. (2008) demonstrated case illustrations for facility layout and dispatching rules selection problem by using grey relational analysis with Data Envelopment Analysis (DEA). Lin et al. (2008) considered TOPSIS technique integrating with the concepts of grey number to deal with the ambiguous information, adopted a subcontractor selection problem. Wu and Olson (2010) presented a grey related fuzzy set methodology incorporating data envelopment analysis as a way to more objectively rank the alternatives. The method was demonstrated on a multi-attribute siting problem.

Turskis and Zavadskas (2010) constituted a novel decision making method 'Grey Additive Ratio Assessment' (ARAS-G) for the selection of a potential supplier and recommended that this technique could be useful to validate the selection of effective alternative of sustainable progress, impact on technologies, investments, structures, environment etc. Stanujkic et al. (2012) combined the concept of interval grey numbers and MOORA method to resolve many complex real-world decision making problems. LI and Zhao (2015) used a stochastic interval-grey number based VIKOR method for multi-criteria decision making, This paper provided a VIKOR method based on prospect theory in which probabilities and the attribute values were both expressed in grey numbers. Kuang et al. (2015) established a Grey-based PROMETHEE II for evaluation of source water protection strategies.

Most of the traditional decision making tools do not consider risk attitude of the decision maker. In contrast, TODIM is a MCDM technique based on risk aversion (attitude) in case of gain and risk seeking (attitude) in case of loss. TODIM is a distinct multi-criteria decision making technique constructed on the base of prospect theory. The TODIM method has been effectively used and factually endorsed in many multi-criteria decision making problems. The shape of the value function of TODIM is identical to the prospect theory's gain and loss function (Moshkovich et al., 2011). This is an experimental technique based on in what way individuals make effective choices in risky circumstances. The benefits of using TODIM method in complex decision making problem have already been discussed in **Section 3.1**.

However, traditional TODIM (crisp-TODIM) fails to solve decision making problems that encounter subjective data set. Therefore, an extension of TODIM was proposed to solve decision making problems with uncertain data resulting in fuzzy-TODIM (Krohling and de Souza, 2012). Fuzzy-TODIM approach explores mathematics of fuzzy set theory; can readily and adequately accommodate subjective evaluation criteria in accordance with appropriate gain and loss functions. Aforementioned extension of TODIM under fuzzy environment was further recommended by several authors on different decision making ground to solve intricate problems with ill-defined (vague) data (Zhang and Xu, 2014; Liu and Teng, 2014).

As grey number theory is competent enough to deal with partially known and partially unknown information, it may be a novel effort to extend crisp-TODIM with grey number conceptions to solve decision making problems considering vague data. Literature depicts that crisp-TODIM was extended by using fuzzy set theory previously; on the similar ground, the present work attempts to integrate the traditional TODIM method with grey numbers set theory and to compare the results (ranking order of candidate alternatives) to that of existing grey based decision making approaches (Li's approach, grey-TOPSIS and Jadidi's approach)

### 3.1.2.3 Research Methodology

#### 3.1.2.3.1 Preliminaries of Grey Numbers Set Theory

Grey theory (Ju-Long, 1982), originally developed by Prof. Deng Ju-Long in 1982, has become a very effective method of solving uncertainty problems under discrete data and incomplete information. Some basic definitions regarding relevant mathematical background of grey system, grey set and grey number in grey theory have been reproduced below from (Li et al., 2007b).

**Definition 1:** A grey system (Xia, 2000) is defined as a system containing uncertain information presented by grey number and grey variables. The concept of grey system is shown in Fig. 3.3.

**Definition 2:** Let $X$ be the universal set. Then a grey set $G$ of $X$ is defined by its two mappings

$$\begin{cases} \bar{\mu}_G(x): \ x \to [0,1] \\ \underline{\mu}_G(x): \ x \to [0,1] \end{cases} \tag{3.32}$$

$\bar{\mu}_G(x) \geq \underline{\mu}_G(x), x \in X$, $X = R$, $\bar{\mu}_G(x)$ and $\underline{\mu}_G(x)$ are the upper and lower membership functions in $G$ respectively. When $\bar{\mu}_G(x) = \underline{\mu}_G(x)$, the grey set $G$ becomes a fuzzy set.

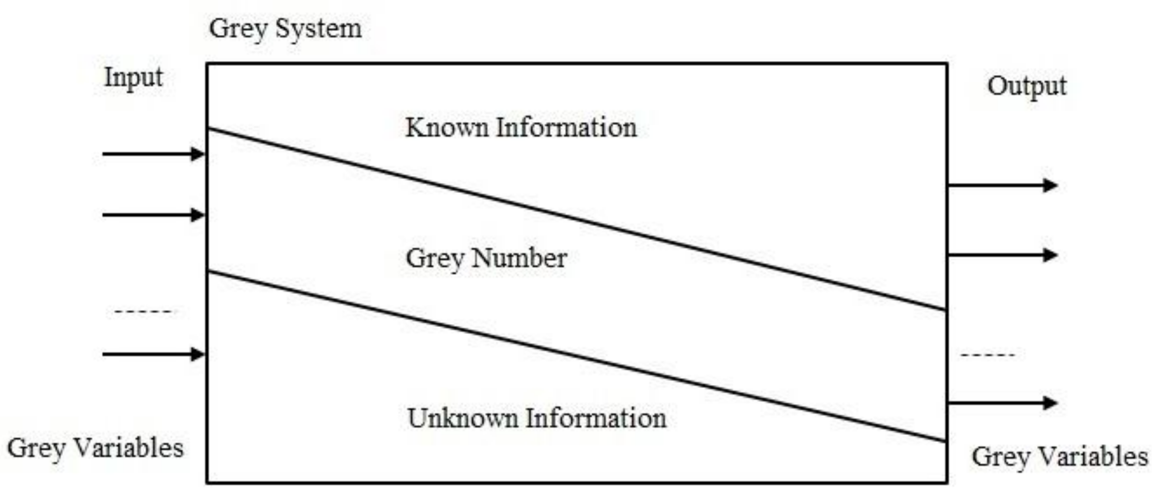


Fig. 3.3: The concept of a grey system

**Definition 3:** A grey number is one of which the exact value is unknown, while the upper and/or the lower limits can be estimated. Generally grey number is written as $\left(\otimes G = G|_{\underline{\mu}}^{\overline{\mu}}\right)$

**Definition 4:** If only the lower limit of $G$ can be possibly estimated and $G$ is defined as lower limit grey number.

$\otimes G = [\underline{G}, \infty]$

**Definition 5:** If only the upper limit of $G$ can be possibly estimated and $G$ is defined as lower limit grey number.

$\otimes G = [-\infty, \underline{G}]$

**Definition 6:** If the lower and upper limits of $G$ can be estimated and $G$ is defined as interval grey number.

$\otimes G = [\underline{G}, \overline{G}]$

**Definition 7:** The basic operations of grey numbers $\otimes G_1 = [\underline{G}_1, \overline{G}_1]$ and $\otimes G_2 = [\underline{G}_2, \overline{G}_2]$ can be expressed as follows:

$$\left.\begin{array}{l}\otimes G_1 + \otimes G_2 = \left[\underline{G}_1 + \underline{G}_2,\ \overline{G}_1 + \overline{G}_2\right] \\ \otimes G_1 - \otimes G_2 = \left[\underline{G}_1 - \overline{G}_2,\ \overline{G}_1 - \underline{G}_2\right] \\ \otimes G_1 \times \otimes G_2 = \min\left[\underline{G}_1\underline{G}_2, \underline{G}_1\overline{G}_2, \overline{G}_1\underline{G}_2, \overline{G}_1\overline{G}_2\right] \\ \qquad\qquad \max\left[\underline{G}_1\underline{G}_2, \underline{G}_1\overline{G}_2, \overline{G}_1\underline{G}_2, \overline{G}_1\overline{G}_2\right] \\ \otimes G_1 \div \otimes G_2 = \left[\underline{G}_1, \overline{G}_1\right] \times \left[\frac{1}{\underline{G}_2}, \frac{1}{\overline{G}_2}\right]\end{array}\right\} \tag{3.33}$$

**Definition 8:** The length of grey number $\otimes G$ is defined as

$$L(\otimes G) = [\overline{G} - \underline{G}] \tag{3.34}$$

**Definition 9:** If $\otimes G_1 = [\underline{G}_1, \overline{G}_1]$ and $\otimes G_2 = [\underline{G}_2, \overline{G}_2]$ are two grey number set then, Euclidean distance between two grey numbers $\otimes G_1$ and $\otimes G_2$ can be calculated by using below equation:

$$d(\otimes G_1, \otimes G_2) = \sqrt{\frac{1}{2}[(\underline{G}_1 - \underline{G}_2)^2 + (\overline{G}_1 - \overline{G}_2)^2]} \tag{3.35}$$

**Definition 10:** The possibility degree $\otimes G_1 \leq \otimes G_2$ of two grey numbers $\otimes G_1 = [\underline{G}_1, \overline{G}_1]$ and $\otimes G_2 = [\underline{G}_2, \overline{G}_2]$ can be expressed as follows (Li et al., 2007b):

$$P\{\otimes G_1 \leq \otimes G_2\} = \frac{\max(0, L^* - \max(0, \overline{G}_1 - \underline{G}_2))}{L^*} \tag{3.36}$$

Here, $L^* = L(\otimes G_1) + L(\otimes G_2)$.

For the position relationship between $\otimes G_1$ and $\otimes G_2$, there exist four possible cases on the real number axis. The relationship between $\otimes G_1$ and $\otimes G_2$ is determined as follows:

1. If $\underline{G}_1 = \underline{G}_2$ and $\overline{G}_1 = \overline{G}_2$, we say that $\otimes G_1$ is equal to $\otimes G_2$ denoted as $\otimes G_1 = \otimes G_2$. Then $P\{\otimes G_1 \leq \otimes G_2\} = 0.5$.

2. If $\underline{G}_2 > \overline{G}_1$, we say that $\otimes G_2$ is larger than $\otimes G_1$, denoted as $\otimes G_2 > \otimes G_1$. Then $P\{\otimes G_1 \leq \otimes G_2\} = 1$.

3. If $\overline{G}_2 < \underline{G}_1$, we say that $\otimes G_2$ is smaller than $\otimes G_1$, denoted as $\otimes G_2 < \otimes G_1$. Then $P\{\otimes G_1 \leq \otimes G_2\} = 0$.

4. If there is an intercrossing part in them, when $P\{\otimes G_1 \leq \otimes G_2\} > 0.5$, it can be said that $\otimes G_2$ is larger than $\otimes G_1$, denoted as $\otimes G_2 > \otimes G_1$. When, $P\{\otimes G_1 \leq \otimes G_2\} < 0.5$, it can be said that $\otimes G_2$ is smaller than $\otimes G_1$, denoted as $\otimes G_2 < \otimes G_1$.

### 3.1.2.4 Grey-TODIM: The Proposed Decision Making Module

The prospect theory function and crisp TODIM can be referred from **Section 3.1.1.3.1** and **Section 3.1.1.3.2** respectively. The procedural steps of grey-TODIM have been summarized as follows:

1. Realization of the decision making problem.
2. Collection of decision making data.
3. Establishing grey multi-attribute decision making matrix.
4. Normalizing grey decision matrix.
5. Computation of partial matrices of dominance and final matrices of dominance.
6. Computation of global measure and derivation of the final ranking order of alternatives.

**Step 1:** Assume that $S = \{S_1, S_2, ..., S_m\}$ is a discrete set of $m$ possible alternatives; also, assume $C = \{C_1, C_2, ..., C_n\}$ is a set of $n$ evaluation criteria/attributes. The attributes are additively independent.

Also consider the attribute weight vector $W = \{w_1, w_2, ..., w_n\}$ and $\sum_{j=1}^{n} w_j = 1$.

**Step 2:** Form a committee of Decision-Makers (DMs) towards assigning ratings of alternatives with respect to various attributes/criteria. Select an appropriate linguistic terms set to be utilized by the DMs for appraising various alternatives with respect to different attributes (Table 3.42). Linguistic expert judgment is to be transformed into appropriate grey numbers (Table 3.43). Individual DMs preferences (grey ratings) are to be aggregated by using the following formulation (Eq. 3.37). Assume that a decision making group consists of $K$ persons; then the aggregated rating $\otimes G_{ij}$ can be computed as:

$$\otimes G_{ij} = \frac{1}{K}[\otimes G_{ij}^1 + \otimes G_{ij}^2 + ... + \otimes G_{ij}^K] \tag{3.37}$$

where, $\otimes G_{ij}^{K}\quad (i=1,2,...,m;\ j=1,2,...,n)$ is the attribute rating given by $K^{th}$ DM which can be described by the grey number $\otimes G_{ij}^{K}=[\underline{G}_{ij}^{K},\overline{G}_{ij}^{K}]$.

**Step 3:** Establish the grey multi-attribute decision-making matrix.

$$\mathbf{D}=\begin{bmatrix}\otimes G_{11} & \otimes G_{12} & \cdots & \otimes G_{1n}\\ \otimes G_{21} & \otimes G_{22} & \cdots & \otimes G_{2n}\\ \vdots & & \ddots & \vdots\\ \otimes G_{m1} & \otimes G_{m2} & \cdots & \otimes G_{mn}\end{bmatrix} \tag{3.38}$$

where $\otimes G_{ij}$ is the aggregated grey rating of $i^{th}$ alternative with respect to $j^{th}$ criterion.

**Step 4:** Normalize the grey decision matrix:

$$\mathbf{D}^{*}=\begin{bmatrix}\otimes G_{11}^{*} & \otimes G_{12}^{*} & \cdots & \otimes G_{1n}^{*}\\ \otimes G_{21}^{*} & \otimes G_{22}^{*} & \cdots & \otimes G_{2n}^{*}\\ \vdots & & \ddots & \vdots\\ \otimes G_{m1}^{*} & \otimes G_{m2}^{*} & \cdots & \otimes G_{mn}^{*}\end{bmatrix} \tag{3.39}$$

For a benefit attribute, $\otimes G_{ij}^{*}$ is expressed as:

$$\otimes G_{ij}^{*}=\left[\frac{\underline{G}_{ij}}{G_{j}^{\max}},\frac{\overline{G}_{ij}}{G_{j}^{\max}}\right]. \tag{3.40}$$

Here, $G_{j}^{\max}=\max_{1\le i\le m}\{\overline{G}_{ij}\}$ (3.41)

For a cost attribute, $\otimes G_{ij}^{*}$ is expressed as:

$$\otimes G_{ij}^{*}=\left[\frac{G_{j}^{\min}}{\overline{G}_{ij}},\frac{G_{j}^{\min}}{\underline{G}_{ij}}\right] \tag{3.42}$$

Here, $G_{j}^{\min}=\min_{1\le i\le m}\{\underline{G}_{ij}\}$ (3.43)

The normalization method mentioned above is to preserve the property that the ranges of the normalized grey number belong to $[0,1]$.

After normalizing the decision matrix, TODIM begins with the calculation of the partial dominance matrices and the final matrices of dominance. For such calculations the DMs need to define firstly a reference criterion, which usually is the criterion with the highest importance weight. So $w_{rc}$ indicates the weight of the criterion $c$ divided by the reference criterion $r$. Here, $w_{rc}$ is also called the trade-off rate (or trade-off weighting factor).

**Step 5:** Computation of partial matrices of dominance and final matrices of dominance. Calculate the dominance of each alternative $A_p$ over each alternative $A_q$ using the following expression:

$$\delta(A_p, A_q) = \sum_{c=1}^{m} \phi_c(A_p, A_q) \quad \forall(p,q) \tag{3.44}$$

where,

$$\phi_c(A_p, A_q) = \begin{cases} \sqrt{\dfrac{w_{rc}}{\sum_{c=1}^{m} w_{rc}} . d(\otimes G_{pc}, \otimes G_{qc})} & If \left[\otimes G_{pc} > \otimes G_{qc}\right] \\ 0, & If \left[\otimes G_{pc} = \otimes G_{qc}\right] \\ -\dfrac{1}{\theta}\sqrt{\dfrac{\sum_{c=1}^{m} w_{rc}}{w_{rc}} . d(\otimes G_{pc}, \otimes G_{qc})} & If \left[\otimes G_{pc} < \otimes G_{qc}\right] \end{cases} \tag{3.45}$$

The term $\phi_c(A_p, A_q)$ represents the contribution of the criterion $c$ to the function $\delta(A_p, A_q)$ when comparing the alternative $p$ with alternative $q$. The parameter $\theta$ represents the attenuation factor of the losses, which can be tuned according to the problem at hand. In this expression, $\otimes G_{pc}$ and $\otimes G_{qc}$ stands for the normalized grey rating against criterion $c$ for two alternatives $A_p$ and $A_q$, respectively. Now, while comparing $\otimes G_{pc}$ and $\otimes G_{qc}$ the concept of grey possibility degree needs to be explored here (**Section 3.1.2.3.1**, **Definition 10**). The term $d(\otimes G_{pc}, \otimes G_{qc})$ designates the distance between the two grey numbers $\otimes G_{pc}$ and $\otimes G_{qc}$, as defined in Eq. (3.35). Three cases can occur in Eq. (3.45):

(i) if the value $\left[\otimes G_{pc} > \otimes G_{qc}\right]$, it represents a gain;

(ii) if the value $\left[\otimes G_{pc} = \otimes G_{qc}\right]$, there is neither loss nor gain and,

(iii) if the value $\left[\otimes G_{pc} < \otimes G_{qc}\right]$, it represents a loss.

The final matrix of dominance is obtained by summing up the partial matrices of dominance of each criterion (Eq. 3.44).

**Step 6:** Calculate the global value of the alternative $p$ by normalizing the final matrix of dominance according to the following expression:

$$\xi_p = \frac{\sum \delta(p,q) - \min \sum \delta(p,q)}{\max \sum \delta(p,q) - \min \sum \delta(p,q)} \tag{3.46}$$

Ordering the values $\xi_p$ provides the rank of each alternative. The best alternatives are those that have higher value $\xi_p$.

### 3.1.2.5 Case Empirical Illustration

In this modern era of industrialization, every organization is utilizing robotic machinery, thereby, ensuring fast completion of work with enhanced accuracy which in turn resulting increased productivity. Productivity growth benefits the organization as well as the employees creating a healthy and supportive work environment within the firm. Robots are well known for performing hazardous task, repetitive movement, annoying job, etc. in a very frequent way. The significant contribution of robots to improve quality and productivity in manufacturing units has gained exceptional appreciation (Liang and Wang, 1993). Robots allow for high flexibility in manufacturing, which makes rapid product changeovers possible. They are intrinsically cleaner than human beings offering improved product quality and reliability, greater consistency, reduced labor costs, reduction of scrap and rework, and reduced floor space requirements (Nnaji and Yannacopoulou, 1988). As the utilization of robots has enormously increased during the past few years; the number of robot manufacturer has also been increased in the marketplace offering different features and characteristics into the robotic systems. Robots are expensive machineries and hence to be chosen carefully to suit particular area of application. Inappropriate selection of robotic machinery may lead to adverse effects towards growth of the organization. Literature depicts glimpses of part research carried out on different aspects of robot selection decision making. A variety of decision support systems have been proposed by pioneers to facilitate evaluation and selection of industrial robots [Wang et al., 1991; Liang and Wang, 1993; Khouja et al., 1995; Bhangale et al., 2004; Rao and

Padmanabhan, 2006; Kumar and Garg, 2010; Chakraborty, 2011; Kentli and Kar, 2011; İç et al., 2013; Liu et al., 2014; Rashid et al., 2014].

Apart from objective data set, aspects of robot selection in presence of subjective criteria/attributes have been attempted through exploration of fuzzy based decision support tools. Literature supports that, apart from fuzzy set theory, grey numbers set can efficiently deal with subjective decision making data. Hence, this section illustrates a case empirical study on robot selection through exploration of TODIM coupled with grey numbers set theory.

### 3.1.2.6 Exploration of Grey-TODIM

In this part of work, a subjective data set has been explored to demonstrate application potential of grey-TODIM approach. Results obtained thereof, has also been compared to that of Li's approach (Li et al., 2007b), Grey-TOPSIS and Jadidi's approach (Jadidi et al., 2008). The following robot selection attributes have been considered here (as shown in Table 3.42): Man-machine interface ($C_1$), Programming flexibility ($C_2$), Vendor's service contract ($C_3$), Purchase cost ($C_4$), Load capacity ($C_5$), and Positioning accuracy ($C_6$). Apart from purchase cost ($C_4$), remaining attributes have been assumed beneficial in nature. However, it seems that purchase cost ($C_4$) and load carrying capacity ($C_5$) are basically objective attributes (quantitative) and their exact data could be available from the robot manufacturer; however, in this analysis, these two attributes have been evaluated subjectively by DMs. Literature supports that aforesaid two attributes have been considered as means of subjectivity in many fuzzy based decision support approaches (Vahdani et al., 2014; Rashid et al., 2014).

A 7-member linguistic terms set has been explored (as shown in Table 3.43) in order to evaluate appropriateness rating of alternative robots with respect to different selection attributes. Priority weights of individual attributes have been expressed in crisp numbers and the values have been presumed. Assuming an expert group (consisting ten DMs) (i.e. $DM_1$… $DM_{10}$) has been involved in this decision making. DMs have been instructed to utilize aforementioned linguistic terms set (Table Table 3.43) to express their judgment in linguistic terminology {Very Low (VL), Low (L), Medium Low (ML), Medium (M), Medium High (MH), High (H), Very High (VH)}. Appropriateness ratings against different robot selection criteria for different robot alternatives ($S_1$, $S_2$, $S_3$, $S_4$) assigned by DMs have been furnished in Table 3.44.

Linguistic ratings as given by the decision-makers have been transformed into appropriate grey numbers in accordance with Table 3.43. Next, aggregated grey performance ratings have been computed against individual criteria for each of the candidate alternatives (by using Eq. 3.37) and shown in Table 3.44. Then, aggregated grey ratings of different attributes with respect to different alternatives have been normalized using Eqs. (3.40-3.43). The normalized decision making matrix has been furnished in Table 3.45.

As per the proposed formulation of grey-TODIM (Eq. 3.45), first, the dominance between the alternative pairs with respect to different criteria needs to be evaluated. As criteria ratings of different alternatives have been expressed in grey numbers, evaluation of the degree of dominance requires the concept of comparing two grey numbers. This could be performed by exploring the concept of grey possibility degree between two grey numbers. Therefore, the grey possibility degree between normalized grey ratings of alternative pairs with respect to different criteria has been computed using Eq. (3.36) and shown in Table 3.46. On the basis of the theory of comparing two grey numbers and from the information obtained from Table 3.46, a realization of gain or loss or no-gain-no-loss between alternative pairs with respect to different criteria has been acquired and shown in Table 3.47. The distance measure for alternative pairs (with respect to a particular criterion) has been treated as the measure of dominance. The distance measure between two alternatives with respect to different criteria has been computed by using Eq. (3.35) and furnished in Table 3.48. By exploring the data from Table 3.48; and the information from Table 3.47; partial matrices of dominance have been constructed using Eq. (3.45) and furnished in Table 3.49.

In this computation, weight for each criterion has been presumed for this sort of robot selection problem, so

$w_1$ = 0.1860, $w_2$ = 0.1860, $w_3$ =0.1396, $w_4$ = 0.1396, $w_5$ = 0.1860, and $w_6$ = 0.1628;

Also, $w_r = 0.1860$ has been assumed as the reference criterion.

Now, the values of $w_{rc}$ (relative weight for each criterion) have been determined as follows.

$w_{r1} = 0.1860/0.1860 = 1,\ w_{r2} = 0.1860/0.1860 = 1,\ w_{r3} = 0.1366/0.1860 = 0.751,$

$w_{r4} = 0.1366/0.1860 = 0.751, w_{r5} = 0.1860/0.1860 = 1,\ w_{r6} = 0.1628/0.1860 = 0.875$

$\sum_{c=1}^{n} w_{rc} = 1+1+0.751+0.751+1+0.875 = 5.38$

The final matrices of dominance have been computed using Eq. (3.44) and presented in Table 3.50. Global measure of alternatives for the different value of $\theta$ $(\theta = 1, 2.5)$ has been calculated using Eq. (3.46) and presented in Table 3.51. The ranking order has finally been achieved using grey-TODIM approach as $S_3 > S_4 > S_2 > S_1$ (for both the values of $\theta$) as shown in Table 3.51.

#### 3.1.2.7 Comparison with Existing Grey Based Decision Making Approaches

The ranking order of alternative robots as obtained through grey-TODIM has been compared to that of other existing grey based decision making approaches. The following sections deal with methodological description of three grey based decision making approaches: Li's approach, grey-TOPSIS and Jadidi's approach.

##### 3.1.2.7.1 Li's Approach

In this approach, the weighted normalized grey decision matrix is to be computed first. Considering different importance (priority weight) of each attribute, the weighted normalized grey decision matrix can be established as:

$$\mathbf{D}_{\mathrm{w}}^{*} = \begin{bmatrix} \otimes V_{11} & \otimes V_{12} & \cdots & \otimes V_{1n} \\ \otimes V_{21} & \otimes V_{22} & \cdots & \otimes V_{2n} \\ \vdots & & \ddots & \vdots \\ \otimes V_{m1} & \otimes V_{m2} & \cdots & \otimes V_{mn} \end{bmatrix}$$

where $\otimes V_{ij} = \otimes G_{ij}^{*} \times w_j$ (3.47)

Now, the ideal alternative is evaluated as a referential alternative. For $m$ possible alternatives set, the ideal referential alternative can be represented by the following notation:

$$S^{\max} = \{\otimes G_1^{\max}, \otimes G_2^{\max}, \otimes G_3^{\max}, \ldots, \otimes G_n^{\max}\} \quad (3.48)$$

This can be obtained by the following relation:

$$S^{\max} = \left\{ \left[ \max_{1\le i\le m} \underline{V}_{i1}, \max_{1\le i\le m} \overline{V}_{i1} \right], \left[ \max_{1\le i\le m} \underline{V}_{i2}, \max_{1\le i\le m} \overline{V}_{i2} \right], ..., \left[ \max_{1\le i\le m} \underline{V}_{in}, \max_{1\le i\le m} \overline{V}_{in} \right] \right\} \tag{3.49}$$

The grey possibility degree between compared alternatives set $S = \{S_1, S_2, S_3, ...., S_m\}$ and the ideal referential alternative $S^{\max}$ can be computed as:

$$P_1 = P\{S_i \le S^{\max}\} = \frac{1}{n} \sum_{j=1}^{n} P\{\otimes V_{ij} \le \otimes G_j^{\max}\} \tag{3.50}$$

Based on $P\{S_i \le S^{\max}\}$ alternatives can be ranked in the order of preference. The philosophy is that when $P\{S_i \le S^{\max}\}$ is smaller, the ranking order of $S_i$ is better.

### 3.1.2.7.2 Grey-TOPSIS

In this part of work, the formulation of grey-TOPSIS as presented by (Oztaysi, 2014) has been utilized by incorporating a minor change in computational part of positive ideal solution and negative ideal solution. In grey-TOPSIS, starting from the weighted normalized decision making matrix (Eq. 3.47), the positive and negative ideal alternatives are to be determined.

The positive ideal alternative $A^+$, and the negative ideal alternative $A^-$, can be defined as:

$$\begin{aligned} A^+ &= \left\{ \left[ \max_{1\le i\le m} \underline{V}_{i1}, \max_{1\le i\le m} \overline{V}_{i1} \right], \left[ \max_{1\le i\le m} \underline{V}_{i2}, \max_{1\le i\le m} \overline{V}_{i2} \right], ..., \left[ \max_{1\le i\le m} \underline{V}_{in}, \max_{1\le i\le m} \overline{V}_{in} \right] \right\} \\ &= \left\{ \otimes V_1^+, \otimes V_2^+, ..., \otimes V_n^+ \right\} \\ &= \left\{ \left( \underline{V}_1^+, \overline{V}_1^+ \right), \left( \underline{V}_2^+, \overline{V}_2^+ \right), ..., \left( \underline{V}_n^+, \overline{V}_n^+ \right) \right\} \end{aligned} \tag{3.51}$$

$$\begin{aligned} A^- &= \left\{ \left[ \min_{1\le i\le m} \underline{V}_{i1}, \min_{1\le i\le m} \overline{V}_{i1} \right], \left[ \min_{1\le i\le m} \underline{V}_{i2}, \min_{1\le i\le m} \overline{V}_{i2} \right], ..., \left[ \min_{1\le i\le m} \underline{V}_{in}, \min_{1\le i\le m} \overline{V}_{in} \right] \right\} \\ &= \left\{ \otimes V_1^-, \otimes V_2^-, ..., \otimes V_n^- \right\} \\ &= \left\{ \left( \underline{V}_1^-, \overline{V}_1^- \right), \left( \underline{V}_2^-, \overline{V}_2^- \right), ..., \left( \underline{V}_n^-, \overline{V}_n^- \right) \right\} \end{aligned} \tag{3.52}$$

Next, the separation measure of the positive and negative ideal alternatives, $d_i^+$ and $d_i^-$ is computed.

$$d_i^+ = \sum_{j=1}^{m} \sqrt{\frac{1}{2}\left[ \left( \underline{V}_j^+ - \underline{V}_{ij} \right)^2 + \left( \overline{V}_j^+ - \overline{V}_{ij} \right)^2 \right]} \tag{3.53}$$

$$d_i^- = \sum_{j=1}^{m} \sqrt{\frac{1}{2}\left[\left(\underline{V}_j^- - \underline{V}_{ij}\right)^2 + \left(\overline{V}_j^- - \overline{V}_{ij}\right)^2\right]} \tag{3.54}$$

The relative closeness, $C_i^+$ to the positive ideal solution is computed by using Eq. (3.55)

$$C_i^+ = \frac{d_i^-}{d_i^+ + d_i^-} \tag{3.55}$$

Here, $0 \le C_i^+ \le 1$. The larger index value is the better evaluation of the alternative. The set of alternatives now can be preferentially ranked by the descending order of the value of $C_i^+$.

### 3.1.2.7.3 Jadidi's Approach

Jadidi et al. (2008) proposed that if $\otimes G_1 = \left[\underline{G}_1, \overline{G}_1\right]$ and $\otimes G_2 = \left[\underline{G}_2, \overline{G}_2\right]$ are two arbitrary interval (grey) numbers, the possibility degree of $\otimes G_1 \ge \otimes G_2$ is expressed as follows:

$$p\{\otimes G_1 \ge \otimes G_2\} = \frac{\max\left(0, L^* - \max(0, \overline{G}_2 - \underline{G}_1)\right)}{L^*} \tag{3.56}$$

Here, $L^* = L(G_1) + L(G_2)$

(Jadidi et al., 2008) combined Li's method (Li et al., 2007b) with the concept of TOPSIS to facilitate grey-based decision making. In order to consider both the positive and the negative ideal solution to evaluate the alternatives, (Jadidi et al., 2008) proposed the following two steps as an extension to Li's approach.

Compute the grey possibility degree between compared alternatives set $S = \{S_1, S_2, ..., S_m\}$ and negative ideal $S^{\min}$ referential alternative in Eq. (3.57) below.

$$P_2 = P\{S_i \ge S^{\min}\} = \frac{1}{n}\sum_{j=1}^{n} p\{\otimes V_{ij} \ge \otimes G_j^{\min}\} \text{ (the larger one is better)} \tag{3.57}$$

Here,

$$S^{\min} = \left\{\left[\min_{1 \le i \le m} \underline{G}_{i1}, \min_{1 \le i \le m} \overline{G}_{i1}\right], ..., \left[\min_{1 \le i \le m} \underline{G}_{in}, \min_{1 \le i \le m} \overline{G}_{in}\right]\right\} \tag{3.58}$$

Find the relative closeness of each alternative to the ideal solution, which is defined in-

Eq. (3.59).

$$C_i = \frac{P_1}{P_2} \tag{3.59}$$

$P_1$ can be obtained by using Eq. (3.50). The alternatives are then ranked based on $C_i$. The alternative with minimum $C_i$ is better. According to the above procedure, the ranking order of candidate alternatives can be determined; and the best from amongst a set of candidate alternatives can easily be selected.

### 3.1.2.8 Data Analysis

The robot selection problem as described in **Section 3.1.2.6** has been solved here using Li's approach, grey-TOPSIS and Jadidi's approach. Results have been summarized below.

As per Li's approach, exploring the data from normalized decision matrix (Table 3.45) and the criteria weights as presented in the earlier section, the weighted normalized decision matrix has been constructed (using Eq. 3.47) as shown in Table 3.52. For the given alternatives set, the ideal (referential) alternative $S^{\max}$ has been characterized by using Eqs. (3.48-3.49).

$\otimes G_1^{\max} = [0.14, 0.19]$, $\otimes G_2^{\max} = [0.13, 0.19]$, $\otimes G_3^{\max} = [0.10, 0.14]$, $\otimes G_4^{\max} = [0.11, 0.14]$

$\otimes G_5^{\max} = [0.14, 0.19]$, $\otimes G_6^{\max} = [0.12, 0.16]$

Now, the grey possibility degree (denoted as $P_1$) between alternative robots ($S_i$ = 1, 2, 3 and 4) and the ideal referential robot alternative $S^{\max}$ has been determined (Table 3.53). According to Eq. (3.50), the value $P\{S_i \le S^{\max}\}$ and the final ranking order have been obtained as shown in Table 3.54. The ranking order appears as: $S_3 > S_4 > S_1 > S_2$.

As per grey-TOPSIS, from the weighted normalized decision making matrix (Table 3.52), the positive ideal solution $A^+$, and the negative ideal solution $A^-$ have been determined by using Eq. (3.51) and Eq. (3.52), respectively as shown in Table 3.55. Next, the separation measures for individual alternatives with respect to both positive ideal solution and negative ideal solution have been computed by using Eq. (3.53) and Eq. (3.54), respectively and shown in Table 3.56. Now, the relative closeness for each alternative, $C_i^+$ with respect to the positive ideal solution has been obtained by using Eq.

(3.55) and shown in (Table 3.56). The final ranking order by applying grey-TOPSIS has been presented in Table 3.56. The ranking order appears as: $S_3>S_2>S_1>S_4$.

As per Jadidi's approach, (from Table 3.52) the grey possibility degree (denoted as $P_1$) between compared alternatives set $S=\{S_1,S_2,...,S_m\}$ and positive ideal $S^{\max}$ referential alternative has been computed using Eq. (3.50). Also, the grey possibility degree (denoted as $P_2$) between compared alternatives set $S=\{S_1,S_2,...,S_m\}$ and negative ideal $S^{\min}$ referential alternative has been computed using Eq. (3.57). In this computation, $S^{\max}$ and $S^{\min}$ has been ascertained using Eq. (3.49) and Eq. (3.58), respectively. Grey possibility degrees for Jadidi's approach (with respect to both $S^{\max}$ and $S^{\min}$) i.e. $P_1$ and $P_2$ thus computed have been shown in Table 3.57. Relative closeness $C_i$ of each alternative with respect to the ideal solution has been computed using Eq. (3.59). The final ranking order of robot alternatives has appeared as $S_3>S_2>S_4>S_1$. Table 3.58 also shows a comparison on the ranking order obtained by using four different decision making approaches for the same robot selection problem. In all cases, the most appropriate choice has appeared the same.

#### 3.1.2.9 Concluding Remarks

In this part of work, TODIM method has been extended by integrating with grey numbers set theory to facilitate decision making involving subjective evaluation criteria. A case empirical study on selection of industrial robotic system has been reported here to exhibit application procedural steps of grey-TODIM. The ranking order of alternative robots as obtained by grey-TODIM has been compared to that of existing grey based decision making approaches [Li's approach (Li et al., 2007b), grey-TOPSIS, Jadidi's approach (Jadidi et al., 2008)]. In all cases, the most appropriate choice has appeared the same. It has been observed that, apart from the most preferred alternative robot, the preference order of other alternatives slightly differs. This may be due to the fact that different approaches follow different philosophy in evaluating the performances of the set of candidate alternatives.

The outcome of the aforesaid research have been summarized below.

1. Integration of grey set theory (grey mathematics, operational rules of grey numbers, grey possibility degree, distance measures between two grey numbers) with traditional TODIM to facilitate decision making under subjective data set.

2. The theory of grey possibility degree has been explored here to realize gain/loss (or no gain no loss) between alternative pairs with respect to a particular criterion.

3. The proposed formulation of grey-TODIM can consider risk attitude of the decision maker. Different values of $\theta$ (the attenuation factor) provides similar ranking order; this ensures robustness of the proposed approach.

In this work, TODIM combined with grey set theory has been case illustrated through a robot selection example. Result obtained thereof, has also been compared to that of various grey based decision support systems available in existing literature. Traditional TODIM can deal with decision making problems involving objective (quantitative) data set only. Literature depicts that TODIM has been extended to work under fuzzy environment. Literature is providing immense evidence that the decision making problems involving subjective (qualitative) data can fruitfully be handled through Fuzzy-TODIM. Similar to fuzzy set theory, grey set theory can also be utilized to facilitate decision making problems in which subjective evaluation information comprises of vague unclear human judgment. With this motivation, the aforesaid work aimed to extend TODIM to be operated under grey environment. The efficacy of the proposed grey-TODIM has been compared to the existing grey based decision support modules.

Table 3.42: Alternative selection criterions

| Goal | Criterions | Notations |
|---|---|---|
| Alternative Evaluation-selection | Man-machine interface | $C_1$ |
| | Programming flexibility | $C_2$ |
| | Vendor's service contract | $C_3$ |
| | Purchase cost | $C_4$ |
| | Load capacity | $C_5$ |
| | Positioning accuracy | $C_6$ |

Table 3.43: Seven-member linguistic terms and their corresponding grey numbers

| Linguistic terms for ratings | $\otimes G$ |
|---|---|
| Very Low (VL) | [0, 1] |
| Low (L) | [1, 3] |
| Medium Low (ML) | [3, 4] |
| Medium (M) | [4, 5] |
| Medium High (MH) | [5, 6] |
| High (H) | [6, 9] |
| Very High (VH) | [9, 10] |

[Source: Li et al., 2007b]

Table 3.44: Appropriateness rating of criterions assigned by the decision-makers and evaluated aggregated grey ratings

| Attributes ($C_i$) | Alternative; $S_i$ | Subjective performance ratings (in linguistic term) given by the Decision-Makers | | | | | | | | | | Aggregated grey ratings |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $DM_1$ | $DM_2$ | $DM_3$ | $DM_4$ | $DM_5$ | $DM_6$ | $DM_7$ | $DM_8$ | $DM_9$ | $DM_{10}$ | |
| $C_1$ | $S_1$ | VH | H | VH | VH | VH | H | H | H | H | H | [7.20, 9.40] |
| | $S_2$ | M | MH | MH | MH | H | H | MH | H | H | H | [5.40, 7.40] |
| | $S_3$ | H | H | H | H | H | H | VH | H | H | H | [6.30, 9.10] |
| | $S_4$ | MH | M | M | M | M | MH | M | M | M | M | [4.20, 5.20] |
| $C_2$ | $S_1$ | VH | H | H | VH | H | H | H | H | H | H | [6.60, 9.20] |
| | $S_2$ | M | MH | M | M | H | H | MH | H | H | H | [5.20, 7.20] |
| | $S_3$ | H | H | H | H | H | H | H | H | H | H | [6.00, 9.00] |
| | $S_4$ | ML | L | L | L | ML | ML | ML | ML | M | M | [2.60, 3.90] |
| $C_3$ | $S_1$ | H | H | MH | MH | MH | H | H | H | H | H | [5.70, 8.10] |
| | $S_2$ | VH | VH | VH | H | H | H | H | H | H | H | [6.90, 9.30] |
| | $S_3$ | H | H | H | H | H | H | VH | H | H | H | [6.30, 9.10] |
| | $S_4$ | MH | MH | H | H | H | MH | H | H | H | H | [5.70, 8.10] |
| $C_4$ | $S_1$ | VH | H | H | H | H | H | H | H | H | H | [6.30, 9.10] |
| | $S_2$ | H | H | H | H | H | H | VH | H | H | H | [6.30, 9.10] |
| | $S_3$ | H | MH | H | H | H | MH | H | H | H | H | [5.80, 8.40] |
| | $S_4$ | M | ML | ML | ML | ML | M | M | M | M | M | [3.60, 4.60] |
| $C_5$ | $S_1$ | MH | M | M | MH | M | MH | M | M | M | M | [4.30, 5.30] |
| | $S_2$ | H | H | H | H | H | H | H | H | H | H | [6.00, 9.00] |
| | $S_3$ | MH | MH | M | M | H | H | MH | H | H | H | [5.30, 7.30] |
| | $S_4$ | VH | VH | VH | H | H | H | H | H | H | H | [6.90, 9.30] |
| $C_6$ | $S_1$ | M | ML | L | L | ML | M | M | M | M | M | [3.20, 4.40] |
| | $S_2$ | MH | M | M | M | M | MH | M | M | M | M | [4.20, 5.20] |
| | $S_3$ | H | H | H | H | H | VH | VH | VH | H | H | [6.90, 9.30] |
| | $S_4$ | MH | MH | MH | MH | MH | H | MH | H | H | H | [5.40, 7.20] |

Table 3.45: Normalized decision making matrix

| $S_i$ | Normalized decision making matrix $\otimes G_{ij}^{*}$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $S_1$ | [0.77,1.00] | [0.72,1.00] | [0.61,0.87] | [0.40,0.57] | [0.46,0.57] | [0.34,0.47] |
| $S_2$ | [0.57,0.79] | [0.57,0.78] | [0.74,1.00] | [0.40,0.57] | [0.65,0.97] | [0.45,0.56] |
| $S_3$ | [0.67,0.97] | [0.65,0.98] | [0.68,0.98] | [0.43,0.62] | [0.57,0.78] | [0.74,1.00] |
| $S_4$ | [0.45,0.55] | [0.28,0.42] | [0.61,0.87] | [0.78,1.00] | [0.74,1.00] | [0.58,0.77] |

Table 3.46: Grey possibility degree between normalized grey ratings of alternative pairs with respect to different criterions

| Alternatives pairs | $P\{\otimes G_{pc} \leq G_{qc}\}$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $S_1$, $S_2$ | 0.04 | 0.12 | 0.75 | 0.50 | 1.00 | 0.92 |
| $S_1$, $S_3$ | 0.38 | 0.43 | 0.66 | 0.61 | 1.00 | 1.00 |
| $S_1$, $S_4$ | 0.00 | 0.00 | 0.50 | 1.00 | 1.00 | 1.00 |
| $S_2$, $S_1$ | 0.96 | 0.88 | 0.25 | 0.50 | 0.00 | 0.08 |
| $S_2$, $S_3$ | 0.77 | 0.76 | 0.43 | 0.61 | 0.25 | 1.00 |
| $S_2$, $S_4$ | 0.00 | 0.00 | 0.25 | 1.00 | 0.60 | 1.00 |
| $S_3$, $S_1$ | 0.62 | 0.57 | 0.34 | 0.39 | 0.00 | 0.00 |
| $S_3$, $S_2$ | 0.23 | 0.24 | 0.57 | 0.39 | 0.75 | 0.00 |
| $S_3$, $S_4$ | 0.00 | 0.00 | 0.34 | 1.00 | 0.91 | 0.07 |
| $S_4$, $S_1$ | 1.00 | 1.00 | 0.50 | 0.00 | 0.00 | 0.00 |
| $S_4$, $S_2$ | 1.00 | 1.00 | 0.75 | 0.00 | 0.40 | 0.00 |
| $S_4$, $S_3$ | 1.00 | 1.00 | 0.66 | 0.00 | 0.09 | 0.93 |

Table 3.47: Realization of grain or loss or no-gain-no-loss between alternative pairs with respect to different criteria

| Alternatives pairs | Relative gain/loss | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $S_1$, $S_2$ | Gain | Gain | Loss | * | Loss | Loss |
| $S_1$, $S_3$ | Gain | Gain | Loss | Loss | Loss | Loss |
| $S_1$, $S_4$ | Gain | Gain | * | Loss | Loss | Loss |
| $S_2$, $S_1$ | Loss | Loss | Gain | * | Gain | Gain |
| $S_2$, $S_3$ | Loss | Loss | Gain | Loss | Gain | Loss |
| $S_2$, $S_4$ | Gain | Gain | Gain | Loss | Loss | Loss |
| $S_3$, $S_1$ | Loss | Loss | Gain | Gain | Gain | Gain |
| $S_3$, $S_2$ | Gain | Gain | Loss | Gain | Loss | Gain |
| $S_3$, $S_4$ | Gain | Gain | Gain | Loss | Loss | Gain |
| $S_4$, $S_1$ | Loss | Loss | * | Gain | Gain | Gain |
| $S_4$, $S_2$ | Loss | Loss | Loss | Gain | Gain | Gain |
| $S_4$, $S_3$ | Loss | Loss | Loss | Gain | Gain | Loss |

* represents no gain and no loss condition

Table 3.48: Distance measure between two alternatives with respect to different criteria

| Alternatives pairs | $d\left(\otimes G_{pc}, \otimes G_{qc}\right)$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $S_1$, $S_2$ | 0.205 | 0.188 | 0.130 | 0.000 | 0.313 | 0.100 |
| $S_1$, $S_3$ | 0.074 | 0.051 | 0.092 | 0.041 | 0.168 | 0.470 |
| $S_1$, $S_4$ | 0.390 | 0.515 | 0.000 | 0.406 | 0.363 | 0.272 |
| $S_2$, $S_1$ | 0.205 | 0.188 | 0.130 | 0.000 | 0.313 | 0.100 |
| $S_2$, $S_3$ | 0.146 | 0.152 | 0.045 | 0.041 | 0.146 | 0.373 |
| $S_2$, $S_4$ | 0.190 | 0.327 | 0.130 | 0.406 | 0.067 | 0.175 |
| $S_3$, $S_1$ | 0.074 | 0.051 | 0.092 | 0.041 | 0.168 | 0.470 |
| $S_3$, $S_2$ | 0.146 | 0.152 | 0.045 | 0.041 | 0.146 | 0.373 |
| $S_3$, $S_4$ | 0.335 | 0.475 | 0.092 | 0.365 | 0.197 | 0.198 |
| $S_4$, $S_1$ | 0.390 | 0.515 | 0.000 | 0.406 | 0.363 | 0.272 |
| $S_4$, $S_2$ | 0.190 | 0.327 | 0.130 | 0.406 | 0.067 | 0.175 |
| $S_4$, $S_3$ | 0.335 | 0.475 | 0.092 | 0.365 | 0.197 | 0.198 |

Table 3.49: Partial matrices of dominance

| Alternatives pairs | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| $S_1$, $S_2$ | 0.195 | 0.187 | -0.965 | 0.000 | -1.298 | -0.786 |
| $S_1$, $S_3$ | 0.117 | 0.098 | -0.813 | -0.543 | -0.950 | -1.699 |
| $S_1$, $S_4$ | -1.449 | 0.309 | 0.000 | -1.705 | -1.397 | -1.292 |
| $S_2$, $S_1$ | -1.050 | -1.006 | 0.135 | 0.000 | 0.241 | 0.128 |
| $S_2$, $S_3$ | 0.165 | -0.905 | 0.079 | -0.543 | 0.165 | -1.514 |
| $S_2$, $S_4$ | -1.010 | 0.246 | 0.135 | -1.705 | -0.601 | -1.036 |
| $S_3$, $S_1$ | 0.117 | -0.526 | 0.113 | 0.076 | 0.177 | 0.276 |
| $S_3$, $S_2$ | 0.165 | 0.168 | -0.566 | 0.076 | -0.886 | 0.246 |
| $S_3$, $S_4$ | -1.343 | 0.297 | 0.113 | -1.618 | -1.028 | 0.180 |
| $S_4$, $S_1$ | -1.449 | -1.664 | 0.000 | 0.238 | 0.260 | 0.210 |
| $S_4$, $S_2$ | -1.010 | -1.326 | -0.965 | 0.238 | 0.112 | 0.169 |
| $S_4$, $S_3$ | 0.250 | -1.598 | -0.813 | 0.226 | 0.191 | -1.104 |

Table 3.50: Final matrices of dominance

| Alternatives | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
|---|---|---|---|---|
| $S_1$ | 0 | -2.667 | -3.79 | -5.535 |
| $S_2$ | -1.553 | 0 | -2.554 | -3.971 |
| $S_3$ | 0.233 | -0.797 | 0 | -3.399 |
| $S_4$ | -2.406 | -2.783 | -2.848 | 0 |

Table 3.51: Global measure of alternatives

| Alternatives | $\sum_{j=1}^{n}\delta(A_i,A_j)$ | $\xi_i$ $(\theta=1)$ | Ranking order | $\sum_{j=1}^{n}\delta(A_i,A_j)$ | $\xi_i$ $(\theta=2.5)$ | Ranking order |
|---|---|---|---|---|---|---|
| $S_1$ | -11.992 | 0.000 | 4 | -5.542 | 0.00 | 4 |
| $S_2$ | -8.078 | 0.487 | 3 | -3.393 | 0.47 | 3 |
| $S_3$ | -3.963 | 1.000 | 1 | -0.98 | 1.00 | 1 |
| $S_4$ | -8.037 | 0.493 | 2 | -3.053 | 0.55 | 2 |

Table 3.52: Weighted normalized decision making matrix

| $S_i$ | Weighted normalized decision making matrix $\otimes V_{ij}$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| Crisp weight | 0.1860 | 0.1860 | 0.1396 | 0.1396 | 0.1860 | 0.1628 |
| $S_1$ | [0.14,0.19] | [0.13,0.19] | [0.09,0.12] | [0.06,0.08] | [0.09,0.11] | [0.06,0.08] |
| $S_2$ | [0.11,0.15] | [0.11,0.15] | [0.10,0.14] | [0.06,0.08] | [0.12,0.18] | [0.07,0.09] |
| $S_3$ | [0.12,0.18] | [0.12,0.18] | [0.09,0.14] | [0.06,0.09] | [0.11,0.15] | [0.12,0.16] |
| $S_4$ | [0.08,0.10] | [0.05,0.08] | [0.09,0.12] | [0.11,0.14] | [0.14,0.19] | [0.09,0.13] |
| $S^{max}$ | [0.14,0.19] | [0.13,0.19] | [0.10,0.14] | [0.11,0.14] | [0.14,0.19] | [0.12,0.16] |

Table 3.53: Computation of grey possibility degree

| $S_i$ | Grey possibility degree $P\{\otimes G_1 \leq \otimes G_2\}$ | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $S_1$ | 0.504 | 0.500 | 0.719 | 1.000 | 1.000 | 1.000 |
| $S_2$ | 0.924 | 0.848 | 0.481 | 1.000 | 0.631 | 1.000 |
| $S_3$ | 0.618 | 0.569 | 0.550 | 1.000 | 0.943 | 0.500 |
| $S_4$ | 1.000 | 1.000 | 0.719 | 0.512 | 0.532 | 0.924 |

Table 3.54: Preference ranking order of alternatives

| $P\{S_i \leq S^{max}\}$ | Grey possibility degree between compared robot's alternatives set | | |
|---|---|---|---|
| | $S_i$ | $P\{S_i \leq S^{max}\}$ | Preference orders |
| $P\{S_1 \leq S^{max}\}$ | $S_1$ | 0.787 | 3 |
| $P\{S_2 \leq S^{max}\}$ | $S_2$ | 0.814 | 4 |
| $P\{S_3 \leq S^{max}\}$ | $S_3$ | 0.697 | 1 |
| $P\{S_4 \leq S^{max}\}$ | $S_4$ | 0.781 | 2 |

Table 3.55: Distance measures of individual alternatives with respect to positive and negative ideal solution

| $S_i$ | Distance measures with respect to positive ideal solution | | | | | |
|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $S_1$ | 0.000 | 0.000 | 0.017 | 0.057 | 0.071 | 0.075 |
| $S_2$ | 0.039 | 0.036 | 0.000 | 0.057 | 0.015 | 0.059 |
| $S_3$ | 0.013 | 0.008 | 0.004 | 0.052 | 0.040 | 0.000 |
| $S_4$ | 0.074 | 0.096 | 0.017 | 0.000 | 0.000 | 0.030 |
| (Positive Ideal Solution) $S^+$ | [0.14,0.19] | [0.13,0.19] | [0.10,0.14] | [0.11,0.14] | [0.14,0.19] | [0.12,0.16] |
| | Distance measures with respect to negative ideal solution | | | | | |
| $S_1$ | 0.075 | 0.096 | 0.004 | 0.000 | 0.000 | 0.000 |
| $S_2$ | 0.038 | 0.061 | 0.017 | 0.000 | 0.054 | 0.012 |
| $S_3$ | 0.065 | 0.088 | 0.012 | 0.005 | 0.027 | 0.073 |
| $S_4$ | 0.000 | 0.000 | 0.000 | 0.055 | 0.063 | 0.040 |
| (Negative Ideal Solution) $S^-$ | [0.08,0.10] | [0.05,0.08] | [0.09,0.12] | [0.06,0.08] | [0.09,0.11] | [0.06,0.08] |

Table 3.56: Separation measures and preference order of alternatives by exploration of TOPSIS-Grey approach

| $S_i$ | Separation measures and preference order of alternative by exploration of TOPSIS-Grey | | | |
|---|---|---|---|---|
| | $d^+$ | $d^-$ | $C^+$ | Preference order |
| $S_1$ | 0.220 | 0.175 | 0.443 | 3 |
| $S_2$ | 0.206 | 0.182 | 0.469 | 2 |
| $S_3$ | 0.117 | 0.270 | 0.698 | 1 |
| $S_4$ | 0.217 | 0.158 | 0.421 | 4 |

Table 3.57: Evaluated grey possibility degree

| $S_i$ | Grey possibility degree $P\{\otimes G_1 \leq \otimes G_2\}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $P_1\{S_i \leq S^{max}\}$ |
| $S_1$ | 0.50 | 0.50 | 0.71 | 1.00 | 1.00 | 1.00 | 0.785 |
| $S_2$ | 0.89 | 0.80 | 0.50 | 1.00 | 0.64 | 1.00 | 0.805 |
| $S_3$ | 0.64 | 0.58 | 0.56 | 1.00 | 0.89 | 0.50 | 0.695 |
| $S_4$ | 1.00 | 1.00 | 0.71 | 0.50 | 0.50 | 0.88 | 0.765 |
| $S_i$ | Grey possibility degree $P\{\otimes G_1 \geq \otimes G_2\}$ | | | | | | $P_2\{S_i \leq S^{min}\}$ |
| $S_1$ | 1.00 | 1.00 | 0.50 | 0.50 | 0.50 | 0.50 | 0.667 |
| $S_2$ | 1.00 | 1.00 | 0.60 | 0.50 | 1.00 | 0.75 | 0.808 |
| $S_3$ | 1.00 | 1.00 | 0.63 | 0.60 | 1.00 | 1.00 | 0.872 |
| $S_4$ | 0.50 | 0.50 | 0.50 | 1.00 | 1.00 | 1.00 | 0.750 |

Table 3.58: Comparison on ranking order

| $S_i$ | Li's approach (Li et al., 2007b) | | Grey-TOPSIS | | Jadidi's approach (Jadidi et al., 2008) | | Grey-TODIM | |
|---|---|---|---|---|---|---|---|---|
| | $P\{S_i \leq S^{max}\}$ | Preference order | $C^+$ | Preference order | $C_i = \frac{P_1}{P_2}$ | Preference order | $\xi_i\ (\theta = 1)$ | Preference order |
| $S_1$ | 0.787 | 3 | 0.443 | 3 | 1.178 | 4 | 0.000 | 4 |
| $S_2$ | 0.814 | 4 | 0.469 | 2 | 0.995 | 2 | 0.487 | 3 |
| $S_3$ | 0.697 | 1 | 0.698 | 1 | 0.797 | 1 | 1.000 | 1 |
| $S_4$ | 0.781 | 2 | 0.421 | 4 | 1.020 | 3 | 0.493 | 2 |

# 3.2 Extension of PROMETHEE for Robot Selection: Simultaneous Exploration of Objective Data and Subjective (Fuzzy) Data

## 3.2.1 Coverage

Robot selection is basically a task of choosing appropriate robot amongst available alternatives with respect to some evaluation criteria. The task becomes much more complicated; apart from objective criteria a number of subjective criteria need to be evaluated simultaneously. Plenty of decision support systems have been well documented in existing literature which considers either objective or subjective data set; however, decision support module with simultaneous consideration of objective as well as subjective data has rarely been attempted before. Motivated by this, present work exhibits application potential of PROMETHEE (extended to operate under fuzzy environment in presence of subjective data) to solve decision making problems which encounter both objective as well as subjective evaluation data. An empirical case study has been demonstrated in the context of robot selection problem. Finally, a sensitivity analysis has been performed to make the robot selection process more robust. A trade-off between objective criteria measure and subjective criteria measure has also been shown using sensitivity analysis.

## 3.2.2 Background and Problem Statement

A robot is a power driven self-controlled programmable machine made with mechanical, microelectronic and electrical components that can repeatedly perform often complicated and monotonous tasks. As per the *American Robots Association*, a robot can be characterized as a multi-functional structure, which can be better controlled by programs and commands (Mondal and Chakraborty, 2013). During the last decades, the use of robotic systems in commercial ventures and production units has been expanded considerably with a perspective to utilize the resources well in time for enhancing efficiency and to improve product quality. Since robots are very expensive structures, so a detailed study for the pertinent robot selection must be carried out carefully. It is commonly agreed from the literature that the maximum possible number of criteria both subjective and objective should be considered for authentic decision making. Robot selection has definitely been a critical issue for assembling organizations in order to enhance part quality and to build profitability. The robot choice criteria may be objective, subjective or blending of both.

Nowadays, several kind of robots which can perform repetitive, hazardous and difficult tasks are readily available in the marketplace with unique features and specification, presumably for all means of application like loading-unloading, assembly, material handling, welding, spray painting, etc. (Kumar and Garg, 2010). Apart from these, robotic packaging and robotic dispensing are some emerging applications of robots in manufacturing industries nowadays. Robot selection is a complicated decision making process in the Multi-Criteria Decision Making (MCDM) framework. Hence, many of the past researchers have explored numerous ways to solve this complexity. Information available for this sort of selection may be objective or subjective in nature, and it is generally accepted that multi-criteria evaluation using objective information is quite handy than the subjective information based analysis.

Braglia and Petroni (1999) applied Data Envelopment Analysis (DEA) towards selection of industrial robots. This methodology is based on a sequential dual use of DEA with restricted weights. The purpose of this research was to identify an optimal robot in a cost/benefit perspective, by measuring the relative efficiency of each robot through the resolution of linear programming problems. Bhangale et al. (2004) endeavored to produce a reliable and comprehensive database of robot controllers based on their different pertinent attributes. This database could be utilized to standardize the robot choice strategy for a specific operation. Bhattacharya et al. (2005) delineated an integrated model combining AHP (Analytical Hierarchy Process) and QFD (Quality Function Deployment) for the industrial robot selection problem. Rao and Padmanabhan (2006) added to a technique based on digraph and matrix methods for assessment of alternative industrial robots. A robot determination index was suggested that could evaluate and rank robots for a given industrial application. Chatterjee et al. (2010) proposed a dual approach to tackle the robot selection issue utilizing two most applicable multi-criteria choice making methods and equated their relative performance for a given industrial application. Initially '*VIsekriterijumsko KOmpromisno Rangiranje*' (VIKOR), a compromise ranking method was used followed by '*ELimination and Et Choice Translating REality*' (ELECTRE), an outranking technique. Kumar and Garg (2010) developed a deterministic quantitative model based on Distance Based Approach (DBA) technique for assessment, determination and ranking of robots. Kentli and Kar (2011) applied a multi-criteria decision making model for a robot selection issue. The proposed model comprised a satisfaction function to transform various robot attributes into a unified scale. Further, a distance measure technique was used to determine the highest ranked candidate robot.

Due to the involvement subjective attributes, robot selection decision making often relies on the subjective judgment of the decision making group. In the decision making process, people usually confront with ambiguity and uncertainty for evaluating the criteria weights and alternatives of the problem (Ghorabaee, 2016). The subjectivity of linguistic human perception is often vague, imprecise and incomplete in nature. Fuzzy logic (Zadeh, 1965; Kapoor and Tak, 2005) has the capability of dealing with such inconsistent evaluation information efficiently.

Numerous studies have been done by the pioneers to extend traditional decision making tools and techniques to operate under fuzzy environment so as to cope up with subjective evaluation information in the context of real world decision making scenario. Fuzzy numbers set hypothesis, can be incorporated into traditional MCDM strategies to acquire the best acceptable preference order with the case where the data set is either subjective entirely or a combination of subjective and objective input. Past researchers utilized fuzzy set hypothesis intermittently with conventional MCDM approaches resulting Fuzzy-TOPSIS, Fuzzy-VIKOR, Fuzzy-MOORA, Fuzzy-ELECTRE, Fuzzy-PROMETHEE, etc.

In the context of robot selection, (Wu, 1990) developed a decision support system for robot selection using fuzzy set approach. Liang and Wang (1993) proposed a robot selection algorithm by combing the concepts of fuzzy set theory and hierarchical structure analysis. The stated methodology was used to aggregate the Decision-Maker's fuzzy response about criteria weigh and the suitability ratings of a robot against various selection criteria to acquire fuzzy suitability indices. Parkan and Wu (1999) exhibited the aspects of Multi-Attribute Decision Making (MADM) and performance measurement methods through a robot selection problem. Emphasis was placed on a performance measurement procedure called operational competitiveness rating (OCRA), and an MADM tool called TOPSIS (*Technique for Order Preference by Similarity to Ideal Solution*). A rank-relationship test demonstrated that the systems could produce comparable rankings for the robots, and final choice was made on the premise of the rankings obtained by averaging the consequences of OCRA, TOPSIS, and a utility model. Chu and Lin (2003) anticipated fuzzy-TOPSIS method where the ratings of alternatives versus subjective criteria and the weights of all criteria were assessed in linguistic terms and characterized by fuzzy numbers.

Kapoor and Tak (2005) executed fuzzy application along with an Analytical Hierarchy Process (AHP) for appropriate robot selection. This paper proposed an integrated methodology for solving common robot selection problems using a modification of the conventional AHP along with 'Fuzzy Linguistic Variables' in place of numbers. Rao et al. (2011) proposed a subjective and objective integrated multiple attribute decision making method for the purpose of robot selection. The method considered objective weights of the attributes as well as the subjective preferences of the Decision-Makers to decide the integrated weight of importance of the attributes. The method used fuzzy logic to convert the qualitative attributes into the quantitative ones. Devi (2011) attempted to solve multiple criteria decision making problems in relation to robot selection by exploring VIKOR method extended in intuitionistic fuzzy environment, in which the weights of criteria and ratings of alternatives were taken as triangular intuitionistic fuzzy numbers set.

Koulouriotis and Ketipi (2011) attempted a fuzzy digraph method for robot evaluation and selection, rendering to a given industrial application. All the information about the objective and subjective attributes were articulated in linguistic terms and represented by fuzzy numbers. The methodology was resolved by converting the fuzzy output into an equivalent crisp value and estimating the selection index. Bai and Wang (2013) proposed an effective weight estimation method in order to make objective and reliable approximation, and thereby, established a fuzzy multiple criteria decision making (FMCDM) model to evaluate, identify and select an optimal robot system to perform the desired task from a large number of robotic systems.

İç et al. (2013) developed a two-phase robot selection decision support system known as ROBSEL. In development of ROBSEL, an independent set of criteria was obtained first and arranged in the Fuzzy Analytical Hierarchy Process (FAHP) decision hierarchy. In the first elimination phase of the decision support system, the user could obtain the feasible set of robots by providing limited values for the requirements under consideration. ROBSEL could then use FAHP decision hierarchy to rank the feasible robots in the second phase. Liu et al. (2014) proposed an interval 2-tuple linguistic TOPSIS (ITL-TOPSIS) method to handle the robot selection problem under uncertain and incomplete information environment. The major advantage of this method was that it could consider both subjective judgments and objective information in real-life applications.

Rashid et al. (2014) suggested a robot selection approach by using generalized Interval-Valued Fuzzy Numbers (IVFN) with TOPSIS and reported that GITFN (Generalized Interval-Valued Triangular Fuzzy Number)-TOPSIS ((*Technique for Order Preference by Similarity to Ideal Solution*) produced satisfactory results by providing two ideal separation and anti-ideal separation matrices. Vahdani et al. (2014) applied a complex proportional assessment method (COPRAS) under an interval-valued fuzzy environment for robot selection. This method enhanced and extended the theory and concept of fuzzy compromise programming based on positive and negative ideal solutions as well as the fuzzy utility degree. Bairagi et al. (2014) employed three Fuzzy Multi-Criteria Decision Making (FMCDM) methodologies in the evaluation and selection of robots for automated foundry operations. In the methodologies, a Fuzzy Analytical Hierarchy Process (FAHP) was integrated individually with a Fuzzy Technique for Order Preference by Similarity to the Ideal Solution (FTOPSIS), a Fuzzy VIsekriterijumska optimizacija i KOmpromisno Resenje (FVIKOR) and a Complex PRoportional ASsessment method with the application of Grey systems theory (COPRAS-G). Parameshwaran et al. (2015) constructed an integrated fuzzy MCDM based approach for robot selection considering objective and subjective criteria. The approach utilized Fuzzy Delphi Method (FDM), Fuzzy Analytical Hierarchical Process (FAHP); Fuzzy modified TOPSIS or Fuzzy VIKOR and Brown–Gibson model for robot selection.

Robot selection is basically a Multi-Criteria Decision Making (MCDM) problem in which the most suitable robot is selected based on some evaluation criteria. Criteria may be objective or subjective or a combination of both. Robot selection considering objective criteria can easily be tackled by traditional decision making tools and techniques. Problem is faced in dealing with subjective criteria since they cannot be assessed by exact numeric score. These criteria are basically ill-defined and vague in nature. This creates uncertainty as well as inconsistency in the decision making as these criteria are assessed by the experts (Decision-Makers). Subjective human judgment often bears ambiguity and vagueness in the decision making; exploration of fuzzy set theory seems fruitful in this context. In fuzzy based decision making approaches, subjective criteria are judged by the experts and assessed in terms of linguistic variables. Linguistic data are further transformed into appropriate fuzzy numbers and finally by exploring fuzzy mathematics, a concrete decision is arrived. In order to tackle subjectivity of the evaluation criteria, traditional decision making tools and techniques have been extended to work under fuzzy environment.

A variety of fuzzy based decision support systems have been proposed by pioneers to solve different decision making problems in different fields of applications. The decision support systems thus reviewed in the existing literature either consider a consolidated objective database or a subjective database. However, rare attempt has been made to support a decision making module considering subjective and objective data base both. To fill up the existing research gap, present study attempts to conceptualize a decision support system considering objective as well as subjective (fuzzy) data in relation to a robot selection problem. The formulations of PROMETHEE I and II have been extended to support the said decision modeling. In later phase of this work, a sensitivity analysis has been performed to make a trade-off between objective factor measures as well as subjective factor measures. In this part of work, objective criteria and subjective criteria have been analyzed separately; and, a global selection score has been computed to select the most appropriate robot in view of variation of the Decision-Makers' risk bearing attitude.

The objectives of the present work are as follows:

1. The research attempts to examine how PROMETHEE method can be explored to analyze objective as well as subjective (fuzzy) evaluation data simultaneously in industrial decision making.
2. In traditional approaches, a decision making data base consisting of objective as well as subjective data cannot be evaluated simultaneously. To get rid of that, either objective data need to be fuzzified and combined with fuzzy data; or, fuzzy data need to be defuzzified (crisp) and analyzed with along with actual objective data. This research proposes an approach to achieve a reliable decision outcome through

simultaneous utilization of objective as well as subjective data without changing their identity.

The research also proposes a novel way (sensitivity analysis) to consider decision-makers' risk bearing attitude in the selection of appropriate alternative

## 3.2.3 Research Methodology

### 3.2.3.1 Preliminaries of Fuzzy Mathematics

Decision making is very much perceived as an intellectual process, normally recognized to diminish the ambiguity and suspicion amongst the numbers of alternatives to make an enlightened choice. It is a conclusive strategic task of making an imperative decision, often executed by manufacturing unit, firms and business houses. To reach any result, Decision-Makers need to access the input response data/information that is of two types like subjective information and objective information. Subjective information can be expressed or communicated through natural language description only, whereas, objective information is a numerical measurement expressed in terms of numbers instead of a natural language description. Objective information can be accessed easily through conventional Multi-Criteria Decision Making (MCDM) methods; however, dealing with the subjective information is a quite challenging task as this information does not acknowledge the explicit situation. Subjective information cannot be utilized until and unless they are converted into some scientific values. For doing so, fuzzy number set theory, was introduced through which subjective attributes can be assessed and represented (Chou et al., 2008).

Fuzzy set theory provides a strict scientific system through which precarious information can be converted into a unified scale precisely. Moreover, it can also be treated as a modeling terminology, strongly recommended for circumstances where fuzzy relationship, criteria, and phenomena exist (Zimmermann, 2010). The Fuzzy set hypothesis can be used in a more extensive way, particularly in the course of information transformation where the situations are vague or imprecise. Essentially, such a framework delivers a usual way of dealing with difficulties in which the source of fuzziness is inherent in the absence of sharply defined criteria of class membership rather than the presence of random variables (Zadeh 1965).

### 3.2.3.2 Definition of Fuzzy Sets

**Definition 1.** A fuzzy set $\tilde{A}$ in a universe of discourse $X$ is characterized by a membership function $\mu_{\tilde{A}}(x)$ which associates with each element $x$ in $X$ a real number in the interval $[0,1]$. The function value $\mu_{\tilde{A}}(x)$ is termed the grade of membership of $x$ in $\tilde{A}$ (Kauffman and Gupta, 1991).

**Definition 2.** A fuzzy set $\tilde{A}$ in a universe of discourse $X$ is convex if and only if

$$\mu_{\tilde{A}}(\lambda x_1 + (1-\lambda)x_2) \geq \min\left(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2)\right) \tag{3.60}$$

For all $x_1, x_2$ in $X$ and all $\lambda \in [0,1]$, where $'\min'$ denotes the minimum operator (Klir and Yuan, 1995).

**Definition 3.** The height of a fuzzy set is the largest membership grade attained by any element in that set. A fuzzy set $\tilde{A}$ in the universe of discourse $X$ is called normalized when the height of $\tilde{A}$ is equal to 1 (Klir and Yuan, 1995).

### 3.2.3.3 Definition of Fuzzy Numbers

**Definition 1.** A fuzzy number is a fuzzy subset in the universe of discourse $X$ that is both convex and normal. Fig. 3.4 shows a fuzzy number $\tilde{n}$ in the universe of discourse $X$ that conforms to this definition (Kauffman and Gupta, 1991).

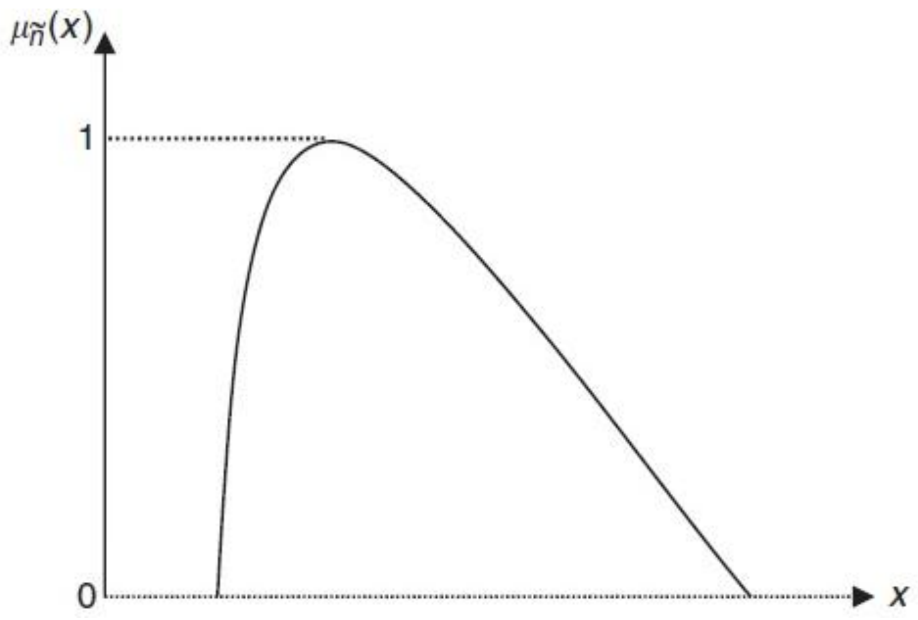


Fig. 3.4: A fuzzy number $\tilde{n}$

**Definition 2.** The $\alpha$ -cut of fuzzy number $\tilde{n}$ is defined as:

$$\tilde{n}^{\alpha} = \{x_i : \mu_{\tilde{n}}(x_i) \geq \alpha, x_i \in X\}, \tag{3.61}$$

Here, $\alpha \in [0,1]$

The symbol $\tilde{n}^{\alpha}$ represents a non-empty bounded interval contained in $X$ , which can be denoted by $\tilde{n}^{\alpha} = [n_l^{\alpha}, n_u^{\alpha}]$, $n_l^{\alpha}$ and $n_u^{\alpha}$ are the lower and upper bounds of the closed interval, respectively (Kauffman and Gupta, 1991; Zimmermann, 1991). For a fuzzy number $\tilde{n}$ , if $n_l^{\alpha} > 0$ and $n_u^{\alpha} \leq 1$ for all $\alpha \in [0,1]$, then $\tilde{n}$ is called a standardized (normalized) positive fuzzy number (Negi, 1989).

**Definition 3.** Suppose, a positive triangular fuzzy number (PTFN) is $\tilde{A}$ and that can be defined as $(a,b,c)$ shown in Fig. 3.5. The membership function $\mu_{\tilde{A}}(x)$ is defined as:

$$\mu_{\tilde{A}}(x) = \begin{cases} (x-a)/(b-a), & if\ a \leq x \leq b, \\ (c-x)/(c-b), & if\ b \leq x \leq c, \\ 0, & otherwise, \end{cases} \tag{3.62}$$

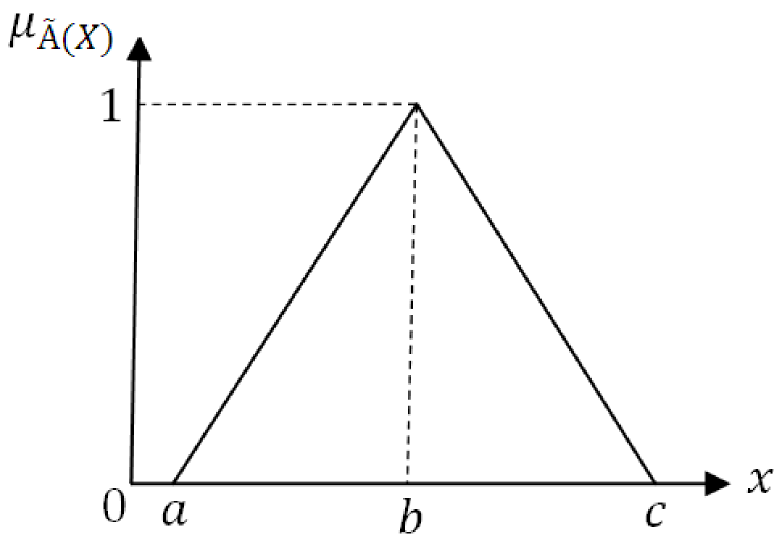


Fig. 3.5: A triangular fuzzy number $\tilde{A}$

Based on extension principle, the fuzzy sum $\oplus$ and fuzzy subtraction $\Theta$ of any two triangular fuzzy numbers are also triangular fuzzy numbers; but the multiplication $\otimes$ of any two triangular fuzzy numbers is only approximate triangular fuzzy number (Zadeh, 1975). Let's have a two positive triangular fuzzy numbers, such as

$\tilde{A}_1 = (a_1, b_1, c_1)$, and $\tilde{A}_2 = (a_2, b_2, c_2)$, and a positive real number $r = (r, r, r)$, some algebraic operations can be expressed as follows:

$$\tilde{A}_1 \oplus \tilde{A}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \tag{3.63}$$

$$\tilde{A}_1 \Theta \tilde{A}_2 = (a_1 - a_2, b_1 - b_2, c_1 - c_2),\ \tilde{A}_1 \otimes \tilde{A}_2 = (a_1 a_2, b_1 b_2, c_1 c_2), \tag{3.64}$$

$$r \otimes \tilde{A}_1 = (ra_1, rb_1, rc_1), \tag{3.65}$$

$$\tilde{A}_1 \varnothing \tilde{A}_2 = (a_1/c_2, b_1/b_2, c_1/a_2), \tag{3.66}$$

The operations of $\vee$ (max) and $\wedge$ (min) are defined as:

$$\tilde{A}_1 (\vee) \tilde{A}_2 = (a_1 \vee a_2, b_1 \vee b_2, c_1 \vee c_2), \tag{3.67}$$

$$\tilde{A}_1 (\wedge) \tilde{A}_2 = (a_1 \wedge a_2, b_1 \wedge b_2, c_1 \wedge c_2), \tag{3.68}$$

Here, $r > 0$, and $a_1, b_1, c_1 > 0$,

Also the crisp value of triangular fuzzy number set $\tilde{A}_i$ can be determined by defuzzification which locates the Best Non-fuzzy Performance (BNP) value. Thus, the BNP values of fuzzy number are calculated by using the center of area (COA) method as follows: (Moeinzadeh and Hajfathaliha, 2010)

$$\text{BNP}_i = \frac{[(c-a)+(b-a)]}{3} + a, \qquad \forall_i \tag{3.69}$$

**Definition 4.** A matrix $\tilde{\mathbf{D}}$ is called a fuzzy matrix if at least one element is a fuzzy number (Buckley, 1985).

### 3.2.3.4 PROMETHEE

The Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE) is a well known and widely used MCDM method. The PROMETHEE method incorporates pairwise comparison and outranking relationship for selection of the best alternatives. The PROMETHEE I (partial ranking) was developed by (Brans, 1982) and presented for the first time in a conference at the Université Laval, Québec, Canada (L'Ingéniérie de la Décision. Elaboration d'instruments d'Aide à la Décision). Further, (Brans and Vincke, 1985) introduced PROMETHEE II method (complete ranking) and constructed a valued outranking graph by using a preference index. Moreover, the authors considered two possibilities to resolve the ranking problem by using this valued graph and also mentioned the difference in the proposed two methods: PROMETHEE I is a partial ranking of the actions and based on the positive and negative flows. It includes indifferences, incomparability and preferences. PROMETHEE II is a complete ranking of the actions and based on the multi-evaluation net flow. It comprises preferences as well as indifferences.

Few years later, Brans et al. (1986) developed PROMETHEE III (ranking based on intervals) and PROMETHEE IV (continuous case). After the development of PROMETHEE method up to the fourth level, Mareschal and Brans, (1988) proposed the visual interactive module GAIA which is capable of providing a marvelous graphical representation supporting the PROMETHEE methodology. Later, (Davignon and Mareschal, 1989) presented numerous real world examples on the application of these methods in the field of health care. PROMETHEE I and II are appropriate, if one of the recognized alternatives needs to be selected; but in the case, where identification of a subset of alternatives is indeed needed under the set of certain constraints, then PROMETHEE series developed yet fails to resolve such sort of problem. In order to fulfil that, PROMETHEE V is developed for that particular case.

Brans and Mareschal (1992; 1995) further suggested two nice extensions: PROMETHEE V (MCDA including segmentation constraints) and PROMETHEE VI (representation of the human brain), in addition to that (Brans and Mareschal, 1994) presented GAIA (Geometrical Analysis for Interactive Assistance) approach, a visual interactive modulation which characterizes a graphic interpretation of the PROMETHEE method. Using GAIA, many effective applications of PROMETHEE method to numerous fields were marked. After the development of PROMETHEE methods in series, a considerable number of successful applications were conducted in various fields such as Banking, Industrial Location, Manpower Planning, Water Resources, Investments, Medicine, Chemistry, Healthcare, Tourism, Ethics in Operations Research, Dynamic management. The success of the methodology is basically due to its mathematical properties and to its friendliness of usage (Brans and Vincke, 1985; Tomic et al., 2011; Velasquez and Hester 2013).

The PROMETHEE family includes PROMETHEE I, II, III, IV, V, VI, PROMETHEE GDSS and PROMETHEE TRI methods. PROMETHEE I provides a partial ranking of the alternatives, Extension II provides a complete ranking with the net flows. Extension III gives the preference and indifference relations using the means and deviations for preference indices. Extension IV accords with a set of infinite alternatives. Extension V is a technique for several selections of alternatives under segmentation constraints (Brans and Mareschal, 1992) and version VI provides representations of the human brain (Brans and Mareschal, 1995). Recently, Behzadian et al. (2010) highlighted two extended approaches on PROMETHEE, called as the PROMETHEE TRI for dealing with sorting problems and the PROMETHEE CLUSTER for nominal classification problems. In addition to that, (Behzadian et al., 2013) applied PROMETHEE Group Decision Support System for selection and ranking of the technical requirements in the House of Quality. Further, (Motlagh et al., 2015) proposed Fuzzy PROMETHEE GDSS for technical requirements ranking in HOQ.

The methods of PROMETHEE were effectively applied in many fields, and a number of researchers used these two extensions of PROMETHEE method in decision making. Macharis et al. (2004) revealed the advantage and disadvantage of the PROMETHEE methodology (outranking methods) over other approaches. First and foremost, the PROMETHEE I method evades trade-offs between scores on criteria, which is expected to happen in Analytic Hierarchy Process (AHP). Though, when the partial ranking is forced into a complete ranking of the alternatives (PROMETHEE II), detailed information might also get misplaced. Secondly, PROMETHEE attains a synthesis indirectly and only requires evaluations to be accomplished on each alternative for each criterion. Equally, in Fuzzy AHP, the synthesis builds directly on the information included in the evaluation matrix that might lead to a substantial amount of pair-wise comparisons to be completed (Brucker et al., 2004). Finally, outranking methods like PROMETHEE are better suited to perform an extensive sensitivity analysis (Turcksin et al., 2011). Espinilla et al. (2015) concluded that among the PROMETHEE family PROMETHEE I and II methods are the most used and well-known in the context of the complex decision making scenario.

Zhang et al. (2009) coupled the concepts of fuzzy sets to represent uncertain site information with the PROMETHEE method. Chen et al. (2011) established a strategic decision making elucidation using fuzzy-PROMETHEE for the case of information system outsourcing. Kuang et al. (2015) established a grey-based PROMETHEE II for evaluation of source water protection strategies. Taillandier and Stinckwich (2011) attempted robot selection using PROMETHEE. The authors concluded that PROMETHEE II method allowed establishing a complete ranking between possible movements based on outranking relations. Experimental results showed that this method could be used to combine effectively the different criteria and outperform several classic exploration strategies.

### 3.2.4 Proposed Decision Support System: Extended PROMETHEE

In this section, the formulations of traditional PROMETHEE approach have been modified so that objective as well as subjective criteria can be utilized simultaneously in course of decision making. Firstly, the procedural hierarchies of two approaches have been documented below (**Section 3.2.4.1** and **Section 3.2.4.2**, respectively) in which (i) one considers subjective weight and objective rating of criteria and (ii) another considers subjective weight and subjective rating of criteria. In later phase, by utilizing aforesaid two approaches, a robot selection decision making problem has been articulated which involves objective as well as subjective evaluation data; weight of each criteria has been expressed subjectively rather than crisp representation. In practice, assignment of exact priority weight is very difficult and therefore, this study assumes that weights are to be given by the decision-makers. Linguistic weights can be transferred into appropriate fuzzy numbers and by using fuzzy aggregation operator; aggregated fuzzy weight against each criterion can be obtained.

#### 3.2.4.1 Consideration of Subjective Weight and Objective Rating of Criteria

In this approach, it has been assumed that the decision making problem involves a set of quantitative (objective) criteria with respect to a finite set of alternatives. Also, criteria weights have been assessed subjectively by the Decision-Makers. The procedural steps of proposed PROMETHEE approach have been depicted as follows.

**Step 1:** Generate a set of feasible alternatives, determine evaluation criteria, and form a group of Decision-Makers (DMs). Suppose $m$ alternatives, $n$ criteria and $k$ decision-makers are involved in the decision making.

**Step 2:** Define a set of linguistic variables and their corresponding representation through triangular fuzzy numbers. Linguistic variables are used to evaluate the importance (weight) of criteria.

A seven-scale linguistic variable fuzzy number has been used to assess the importance of evaluation criteria with a fuzzy set. Table 3.59 shows the linguistic scale and corresponding triangular fuzzy numbers for assignments of criteria weights.

**Step 3:** Aggregate decision-makers evaluations. A decision is derived by aggregating the fuzzy weights of criteria from $n$ decision-makers as calculated by Eq. (3.70).

$$\tilde{w}_j = \frac{1}{k}\left[\sum_{e=1}^{n} \tilde{w}_j^e\right] = \frac{1}{k}\left[\tilde{w}_j^1 + \tilde{w}_j^2 + \ldots + \tilde{w}_j^k\right] \tag{3.70}$$

**Step 4:** Construct a decision matrix $\mathbf{D}$ and compute the aggregated fuzzy weight of criterion.

$$\mathbf{D} = \left[x_{ij}\right]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \ldots & xn \\ x_{21} & x_{22} & \ldots & x_{2n} \\ . & . & . & . \\ x_{m1} & x_{m2} & \ldots & xn \end{bmatrix} (i = 1,2,\ldots,m;\ j = 1,2,\ldots,n) \tag{3.71}$$

$$\tilde{\mathbf{W}} = \left[\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n\right] \tag{3.72}$$

Here $x_{ij}$ is the crisp rating of alternative $A_i$ with respect to criterion $C_j$, and $\tilde{w}_j$ is the aggregated fuzzy weight (computed from Eq. 3.70) of the $j^{th}$ criterion. This study, therefore, denotes $\tilde{w}_j$ as triangular fuzzy number.

**Step 5:** Normalize the decision making matrix denoted by $\mathbf{R}$ is shown as:

$$\mathbf{R} = \left[r_{ij}\right]_{mn} \tag{3.73}$$

$$\mathbf{R} = \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{i1} \\ r_{21} & r_{22} & \ldots & r_{2n} \\ . & . & . & . \\ r_{m1} & r_{m2} & \ldots & r_{mn} \end{bmatrix} (i = 1,2,\ldots,m;\ j = 1,2,\ldots,n) \tag{3.74}$$

The normalization process can be performed by following Eqs. (3.75-3.76)

$$r_{ij} = \frac{x_{ij}}{\underset{i}{Max}\left(x_{ij}\right)},\ i = 1,2,\ldots,m;\ j = 1,2,\ldots,n. \quad \text{(For benefit criteria)} \tag{3.75}$$

$$r_{ij} = \frac{\underset{i}{Min}(x_{ij})}{x_{ij}},\ i = 1,2,...,m;\ j = 1,2,...,n. \quad \text{(For cost criteria)} \tag{3.76}$$

Here, $r_{ij}$ is the normalized value of $i^{th}$ alternative for $j^{th}$ criterion.

**Step 6:** Construct the preference function

Let $A$ be a set of alternatives; $a$ and $b$ are two alternatives of set $A$. Preference function $P_j(a,b)$ can be defined as follows:

$$P_j(a,b) = \begin{cases} 0, & r_{aj} \le r_{bj}, \\ r_{aj} - r_{bj}, & r_{aj} > r_{bj}, \end{cases} \quad j = 1,2,...,n \tag{3.77}$$

Here, the preference function $P_j(a,b)$ is the outranking intensity indicating that $a$ is superior to $b$. Also $r_{ij}$ indicates the normalized rating of the $i^{th}$ alternative with respect to $j^{th}$ criterion. The preference function $P_j(a,b)$ for a criterion $j$ derives, for the difference measures between two evaluations on that particular criterion. The outranking relational constructs from pairwise comparison of alternatives rates.

$$\begin{cases} r_{aj} > r_{bj} & \Leftrightarrow aPb\ (a\ outranks\ b), \\ r_{aj} = r_{bj} & \Leftrightarrow aIb\ (a\ is\ indifferent\ to\ b). \end{cases} \tag{3.78}$$

**Step 7:** Generate the multi-criteria preference index to determine the value of the outranking relation.

If each criterion $C_j\ (j = 1,2,...,n)$ with preference function $P_j$, the multi-criteria preference index $\tilde{\pi}(a,b)$ can be derived as

$$\tilde{\pi}(a,b) = \frac{\sum_{j=1}^{k} \tilde{w}_j P_j(a,b)}{\sum_{j=1}^{k} \tilde{w}_j} \tag{3.79}$$

Here, $\tilde{\pi}(a,b)$ be the multi-criteria preference index expressed in triangular fuzzy number. Also $\tilde{w}_j$ is the aggregated fuzzy weight of $j^{th}$ criterion i.e. $C_j$.

**Step 8:** Calculate the flow to preorder alternatives.

PROMETHEE I: The usage of partial preorder reveals the message which the comparison between some alternatives cannot show. Outgoing/leaving flow is given in Eq. (3.80)

$$\tilde{\varphi}^{+}(a) = \sum_{y \neq a} \tilde{\pi}(a, y), \quad \forall a, y \in A, \tag{3.80}$$

Where $\tilde{\phi}^{+}(a)$ the sum of preferences, indicating that $a$ is superior to other alternatives. As the value $\tilde{\phi}^{+}(a)$ increases, the suitability of alternative $a$ increases.

Incoming/entering flow is given in Eq. (3.81).

$$\tilde{\varphi}^{-}(a) = \sum_{y \neq a} \tilde{\pi}(y, a), \quad \forall a, y \in A, \tag{3.81}$$

Where $\tilde{\varphi}^{-}(a)$ is the sum of preferences, indicating that other alternatives are superior to $a$ As the value of $\tilde{\varphi}^{-}(a)$ is smaller, the suitability of alternative $a$ increases.

The fuzzy values of $\tilde{\phi}^{+}(a)$ and $\tilde{\phi}^{-}(a)$ need to be defuzzifized to get the net flow $\phi(a)$ as depicted in Eq. (3.69).

Then, the preference relation and partial preorder $\left(P^{(I)}, I^{(I)}, R\right)$ are derived as follows:

$$aP^{+}b : \begin{cases} P \ \ if\ \phi^{+}(a) > \phi^{+}(b), \forall a, b \in A, \\ I\ If\ \phi^{+}(a) = \phi^{+}(b), \forall a, b \in A, \end{cases} \tag{3.82}$$

$$aP^{-}b : \begin{cases} P \ \ if\ \phi^{-}(a) < \phi^{-}(b), \forall a, b \in A, \\ I\ If\ \phi^{-}(a) = \phi^{-}(b), \forall a, b \in A, \end{cases} \tag{3.83}$$

Here $\phi^{+}(a)$ and $\phi^{-}(a)$ are the defuzzified values of $\tilde{\phi}^{+}(a)$ and $\tilde{\phi}^{-}(a)$, respectively. Based on the intersection between (Eq. 3.82) and (Eq. 3.83), one can obtain the outranking relation and partial preorder as follows:

$$\begin{cases} aP^{(I)}\ (a\ outranks\ b), \begin{cases} aP^{+}b : P\ and\ aP^{-}b : P, \\ aP^{+}b : P\ and\ aP^{-}b : I, \\ aP^{+}b : I\ and\ aP^{-}b : P, \end{cases} \\ aI^{(I)}b\ (a\ is\ indifferent\ to\ b), aP^{+}b : I\ and\ aP^{-}b : I, \\ aRb\ (a\ and\ b\ are\ incomparable),\ otherwise. \end{cases} \tag{3.84}$$

PROMETHEE II: Compare and rank all alternatives using the complete preorder. This model ranks the alternatives according to their net flows. The definition of net flows $\phi(a)$ is

$$\varphi(a) = \varphi^{+}(a) - \phi^{-}(a),\ \forall a \in A. \tag{3.85}$$

As the value of $\phi(a)$ increases, the suitability of alternative $a$ increase. The preference relation is defined as follows:

$$\begin{cases} aP^{(II)}b\ (a\ outranks\ b)\ If\ \phi(a) > \phi(b), \forall a,b \in A, \\ aI^{(II)}b\ (a\ is\ indifferent\ to\ b)\ If\ \phi(a) = \phi(b), \forall a,b \in A. \end{cases} \tag{3.86}$$

Additionally, in PROMETEE I, the partial preorder can be obtained from leaving and entering flows. In PROMETHEE II, the consideration of net flow leads to a complete ranking.

**Step 9:** Construct a value outranking graph to evaluate the preference rank of each alternative.

#### 3.2.4.2 Consideration of Subjective Weight and Subjective Rating of Criteria

In this section, it has been assumed that the decision making problem is involved with a set of qualitative (subjective) criteria and the importance weight of each criterion is subjectively assessed rather than crisp representation. The procedural steps of the said decision making module have been described below.

**Step 1:** Same as described in **Section 3.2.4.1**

**Step 2:** Define two separate linguistic terms set and their corresponding triangular fuzzy numbers representation to evaluate the importance (weight) of criteria and ratings of alternatives with respect to various criteria. Table 3.59 shows the linguistic scales and corresponding triangular fuzzy numbers for weight of criteria and rating of alternatives, respectively.

**Step 3:** Aggregate Decision-Makers evaluations. A decision is derived by aggregating the fuzzy weights of criteria and fuzzy appropriateness rating of alternatives from $K$ Decision-Makers as calculated by Eq. (3.70). Additionally, the rating of $K$ Decision-

Makers with respect to $j^{th}$ criterion $(C_j)$ of each alternative in the $i^{th}$ alternative $(A_i)$ can be calculated using Eq. (3.87).

$$\tilde{x}_{ij} = \frac{1}{K}\left[\sum_{e=1}^{n} \tilde{x}_{ij}^{e}\right] = \frac{1}{K}\left[\tilde{x}_{ij}^{1} + \tilde{x}_{ij}^{2} + \ldots + \tilde{x}_{ij}^{K}\right] \tag{3.87}$$

**Step 4:** Construct a fuzzy decision matrix $\tilde{\mathbf{D}}$ and compute the aggregated fuzzy weight of criterion.

$$\tilde{\mathbf{D}} = \left[\tilde{x}_{ij}\right]_{m\times n} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \ldots & \tilde{x}_{in} \\ \tilde{x}_{21} & \tilde{x}_{22} & \ldots & \tilde{x}_{2n} \\ . & . & . & . \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \ldots & \tilde{x}_{mn} \end{bmatrix} (i = 1,2,\ldots,m;\ j = 1,2,\ldots,n) \tag{3.88}$$

$$\tilde{\mathbf{W}} = \left[\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n\right]$$

Here, $\tilde{x}_{ij}$ is the aggregated fuzzy rating of alternative $A_i$ with respect to criterion $C_j$ and $\tilde{w}_j$ is the aggregated fuzzy weight of the $j^{th}$ criterion. This study, therefore, denotes linguistic variables $\tilde{x}_{ij}$ and $\tilde{w}_j$ as triangular fuzzy numbers.

**Step 5:** Normalize the fuzzy decision making matrix denoted by $\tilde{\mathbf{R}}$ is shown as:

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{m\times n} \tag{3.89}$$

$$\tilde{R} = \begin{bmatrix} \tilde{r}_{11} & \tilde{r}_{12} & \ldots & \tilde{r}_{ik} \\ \tilde{r}_{21} & \tilde{r}_{22} & \ldots & \tilde{r}_{2k} \\ . & . & . & . \\ \tilde{r}_{m1} & \tilde{r}_{m2} & \ldots & \tilde{r}_{mk} \end{bmatrix} (i = 1,2,\ldots,m;\ j = 1,2,\ldots,n) \tag{3.90}$$

If $(\tilde{x}_{ij}, i = 1,2,\ldots,m;\ j = 1,2,\ldots,n)$ are triangular fuzzy numbers, then the normalization process can be performed by assuming $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$,

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right) (i = 1,2,\ldots,m,\ j \in B,) \tag{3.91}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) (i = 1,2,\ldots,m,\ j \in C,) \tag{3.92}$$

where, $B$ and $C$ are the set of benefit criteria $B$ and cost criteria $C$, respectively, and

$$c_j^* = \max_i c_{ij}\ j \in B, \tag{3.93}$$

$$a_j^- = \min_i a_{ij} \; j \in C. \tag{3.94}$$

**Step 6:** Construct the preference function

Let $A$ be a set of alternatives; $a$ and $b$ are two alternatives of set $A$. Preference function $\tilde{P}_j(a,b)$ can be defined as follows:

$$\tilde{P}_j(a,b) = \begin{cases} 0, & \tilde{r}_{aj} \le \tilde{r}_{bj}, \\ \tilde{r}_{aj} - \tilde{r}_{bj}, & \tilde{r}_{aj} > \tilde{r}_{bj}, \end{cases} \qquad j = 1,2,...,n. \tag{3.95}$$

Here, the preference function $\tilde{P}_j(a,b)$ is the outranking intensity indicating that $a$ is superior to $b$.

The preference function $\tilde{P}_j(a,b)$ for a criterion $j$ derives, for the difference measures between two evaluations on that particular criterion. The outranking relational constructs from pairwise comparison of alternatives rates.

$$\begin{cases} \tilde{x}_{aj} > \tilde{x}_{bj} \Leftrightarrow aPb \; (a\, outranks\, b), \\ \tilde{x}_{aj} = \tilde{x}_{bj} \Leftrightarrow aIb\,(a\, is\, indifferent\, to\, b). \end{cases} \tag{3.96}$$

**Step 7:** Generate the multi-criteria preference index to determine the value of the outranking relation.

If each criterion $C_j \, (j = 1,2,...,n)$ with preference function $\tilde{P}_j$, the multi-criteria preference index $\tilde{\pi}(a,b)$ can be derived as

$$\tilde{\pi}(a,b) = \frac{\sum_{j=1}^{k} \tilde{w}_j \tilde{P}_j(a,b)}{\sum_{j=1}^{k} \tilde{w}_j} \tag{3.97}$$

Here, $\tilde{\pi}(a,b)$ be the multi-criteria preference index expressed in triangular fuzzy number. Also $\tilde{w}_j$ is the aggregated fuzzy weight of $j^{th}$ criterion i.e. $C_j$

**Steps 7-8:** Same as discussed in **<u>Section 3.2.4.1</u>**

### 3.2.5 Case Empirical Illustration

In this empirical illustration, a decision making scenario has been generated for evaluation and selection of industrial robots. For this specific sort of study, a consolidated database considering information in relation to objective criteria as well as subjective criteria have been explored. Based on exhaustive literature review, the criteria list has been selected (Table 3.60). Basically, the work articulates a framework on exploration of extended PROMETHEE with simultaneous consideration of objective as well as subjective data. The application potential of the said approach has been case empirically demonstrated through a robot selection decision making viewpoint. Therefore, the criteria lists as well as the data sets explored here are empirical in nature. However, companies may go through detailed survey regarding necessity and importance of the criteria to be considered for a realistic decision making.

A total number of thirteen criteria have been evaluated with respect to seven choices (alternative robot, in the present case). The criteria includes Load capacity ($C_1$) [Goh et al., 1996; Parkan and Wu, 1999; Khouja and Booth, 1995; Bhangale et al., 2004; Rao and Padmanabhan, 2006; Kumar and Garg, 2010; Chatterjee et al., 2010; Rao et al., 2011; Chakraborty, 2011; Karsak et al., 2012], Repeatability ($C_2$) [Goh et al., 1996; Parkan and Wu, 1999; Khouja and Booth, 1995; Bhangale et al., 2004; Rao and Padmanabhan, 2006; Kumar and Garg, 2010; Chatterjee et al., 2010; Rao et al., 2011; Karsak et al., 2012; Chakraborty, 2011], Maximum tip speed ($C_3$) [Bhangale et al., 2004; Chatterjee et al., 2010; Rao et al., 2011; Mondal and Chakraborty, 2013; Chakraborty, 2011], Memory capacity ($C_4$) [Bhangale et al., 2004; Chatterjee et al., 2010; Rao et al., 2011; Mondal and Chakraborty, 2013; Chakraborty, 2011], Manipulator reach ($C_5$) [Bhangale et al., 2004; Chatterjee et al., 2010; Rao et al., 2011; Mondal and Chakraborty, 2013; Chakraborty, 2011], Man-machine interface ($C_6$) [Chu and Lin, 2003; Rao and Padmanabhan, 2006; Devi, 2011; Vahdani et al., 2014; Rashid et al., 2014], Programming flexibility ($C_7$) [Goh et al., 1996; Chu and Lin, 2003; Rao and Padmanabhan, 2006; Devi, 2011; Vahdani et al., 2014; Rashid et al., 2014], Vendor's service contract ($C_8$) [Goh et al., 1996; Chu and Lin, 2003; Rao and Padmanabhan, 2006; Devi, 2011; Vahdani et al., 2014; Rashid et al., 2014], Positioning accuracy ($C_9$) [Chu and Lin, 2003; Bhangale et al., 2004; Devi, 2011; Vahdani et al., 2014; Rashid et al., 2014], Safety ($C_{10}$) [Bhangale et al., 2004], Environmental performance ($C_{11}$) [Rossetti and Selandari, 2001; Choudhury et al., 2006], Reliability ($C_{12}$) [Bhangale et al., 2004; Choudhury et al., 2006] and Maintainability ($C_{13}$) [Bhangale et al., 2004; Choudhury et al., 2006]. Out of thirteen considered criteria, first five criteria i.e. $C_1$ to $C_5$ have been treated as objective in nature and corresponding numeric values have been collected from past literature (Mondal and Chakraborty, 2013; Omoniwa, 2014). The remaining eight criteria i.e. $C_6$ to $C_{13}$ have been assessed subjectively by the Decision-Makers (DMs). In the known set of attributes (objective criteria), only repeatability has been considered as the non-beneficial attribute (Lower-is-Better; LB) whilst other attributes treated as beneficial (Higher-is-Better; HB) in nature. All the subjective criteria have been considered as beneficial in nature.

A seven member linguistic term set has been chosen for assigning priority weight of the criteria. The linguistic terms set is: {Very Low (VL), Low (L), Medium Low (ML), Medium (M), Medium High (MH), High (H) and Very High (VH)}. Moreover, a separate linguistic term set (7-member) has been adapted for assessing appropriateness rating of various robot alternatives with respect to the subjective criteria. The linguistic term set for rating of subjective criteria is: {Very Poor (VP), Poor (P), Medium Poor (MP), Medium (M), Medium Good (MG), Good (G), and Very Good (VG)}. The linguistic terms and corresponding fuzzy representations have been tabulated in Table 3.59.

In this work, an empirical decision making scenario has been provided to focus application potential of the proposed extended PROMETHEE in consideration with both objective as well as subjective data. The expert team exploited has been basically a hypothetical one. The group members (presumed as four members) are supposed to be the respondents to fill up the questionnaire. In practice, industries may select the Decision-Makers based on their own policy. The group of respondents may include industry personnel, management consultant as well as academician. They must possess enough knowledge and experience in industrial decision making, more precisely in robot selection in the present context.

The decision making committee which consists of four Decision-Makers have been instructed to provide their consent in order to determine the priority weight against individual criterion ($C_1$ to $C_{13}$), and appropriateness rating for each subjective criterion ($C_6$-$C_{13}$) over each alternatives as shown in Table 3.60 and Table 3.61, respectively.

Table 3.62 exhibits data in relation to the objective criteria for individual alternative robots. DMs expert judgment expressed in linguistic terminology has been transformed into appropriate triangular fuzzy numbers in accordance with Table 3.59. Based on Eq. (3.70), aggregated fuzzy weights against criteria $C_1$ to $C_{13}$ have been computed and shown in Table 3.60. Similarly, aggregated fuzzy ratings against subjective criteria $C_6$ to $C_{13}$ have been computed by using Eq. (3.87) and shown in Table 3.61. Considering objective data (collected from Table 3.62) and aggregated fuzzy ratings with respect to subjective criteria (from Table 3.61), the initial decision making matrix has been formed (as shown in Table 3.63).

Normalization of the initial decision matrix has been carried out in two ways as mentioned below. The normalized decision matrix has been represented in Table 3.64. Objective data have been normalized by using Eq. (3.75) for beneficial attributes [$C_1$ to $C_5$], and Eq. (3.76) for non-beneficial attribute(s) [$C_6$ to $C_{13}$]. Aggregated fuzzy ratings for subjective criteria have been normalized by using Eq. (3.91), assuming all criteria have been beneficial in nature. After normalizing the initial decision matrix, multi-criteria preference index for all pair of alternatives has been calculated. The multi-criteria preference function $P_j(a,b)$ between two alternatives $a$ and $b$ for the objective criterion $C_j$ has been computed by using Eq. (3.77); and the multi-criteria preference function $\tilde{P}_j(a,b)$ between two alternatives $a$ and $b$ for the subjective criterion $C_j$ has been computed by using Eq. (3.95). The preference function values [$P_j(a,b)$ when $j$ is objective criterion and $\tilde{P}_j(a,b)$ when $j$ is subjective criterion] thus computed have been furnished in Table 3.65. Now, the multi criteria preference index $\tilde{\pi}(a,b)$ between two alternatives $a$ and $b$ have been computed (by using Eq. (3.79) and Eq. (3.97) and furnished in Table 3.66. Outgoing/leaving flow $\tilde{\phi}^+(a)$, incoming/entering flow $\tilde{\phi}^-(a)$ for different robot alternatives have been computed by using Eq. (3.80), Eq. (3.81) and shown in Table 3.67. The defuzzified values of $\tilde{\phi}^+(a)$ and $\tilde{\phi}^-(a)$ have been computed to get the net flow $\phi(a)$ using Eq. (3.85). Based on net flow $\phi(a)$ alternative robots have been ranked. The ranking order appears as:

$R_1 > R_2 > R_3 > R_5 > R_7 > R_4 > R_6$.

In aforesaid section, alternatives robots have been evaluated based on objective as well as subjective criteria. In later part of this work, a sensitivity analysis has been carried out to make a compromise between objective factor (criteria) measure (OFM) and subjective factor (criteria) measure (SCM). In this section, initially, ranking order of candidate robots has been evaluated by considering objective and subjective criteria separately. Then a compromise selection procedure has been demonstrated to make a trade-off between objective criteria and subjective criteria. In course of sensitivity analysis, the first part is to evaluate robot alternatives by considering objective criteria only. The preference function values [ $P_j(a,b)$ when $j$ is objective criterion] from Table 3.65 have been explored to compute the multi-criteria preference index $\tilde{\pi}(a,b)$ between two alternatives $a$ and $b$ (considering objective criteria only i.e. $C_1$ to $C_5$) by using Eq. (3.79) (Shown in Table 3.68). Table 3.69 shows $\tilde{\phi}^+(a)$ and $\tilde{\phi}^-(a)$ as computed from Eq. (3.80) and Eq. (3.81) and net flow $\phi(a)$ for individual alternatives. The ranking order of alternative robots appears as (Table 3.72): $R_3 > R_1 > R_2 > R_7 > R_4 > R_6 > R_5$.

A separate analysis has also been carried out in order to determine the ranking order of candidate robots by considering subjective criteria only. Exploring the preference function values [ $\tilde{P}_j(a,b)$ when $j$ is subjective criterion] obtained from Table 3.65; the multi-criteria preference index $\tilde{\pi}(a,b)$ between two alternatives $a$ and $b$ (considering subjective criteria only i.e. $C_6$ to $C_{13}$) has been computed (by using Eq. 3.97) and furnished in Table 3.70. Table 3.71 shows $\tilde{\phi}^+(a)$ and $\tilde{\phi}^-(a)$ (computed from Eqs. (3.80-3.81) and net flow $\phi(a)$ for individual alternatives. The ranking order of alternative robots appears as (Table 3.72): $R_2 > R_1 > R_5 > R_3 > R_7 > R_4 > R_6$.

Finally, a Robot Selection Score (RSS) has been obtained by using Eq. (3.98), for alternative robots. Sensitivity analysis plot shows how decision-makers' perception (risk-bearing attitude) influences choice of the most appropriate robot (Ray et al., 2010).

$$(RSS)_i = [\alpha \times SFM_i + (1-\alpha) OFM_i] \tag{3.98}$$

In Eq. (3.98), $(RSS)_i$ is the overall robot selection score for $i^{th}$ robot considering both subjective as well as objective criteria. $SFM_i$ be the subjective factor measure for $i^{th}$ robot i.e. normalized value of $\phi(a)$; whereas, $OFM_i$ be the objective factor measure for $i^{th}$ robot i.e. normalized value of $\phi(a)$ (refer to Table 3.72). In this expression, $\alpha$ is the decision-maker's risk bearing attitude $(0 \leq \alpha \leq 1)$. Considering objective criteria, the net flow $\phi(a)$ values for alternative robots obtained from Table 3.69 have been normalized and treated as OFM in Table 3.72. Similarly, by considering subjective criteria, the net flow $\phi(a)$ values for alternative robots obtained from Table 3.71 have been normalized and treated as OFM in Table 3.72. Finally, RSS has been computed based on Eq. (3.98), for determining appropriate ranking order of candidate robots

Sensitivity analysis plot (Fig. 3.6) reflects that when decision-makers' risk bearing attitude $\alpha$ is approximately up to 0.4, robot $R_3$ is the best. When $\alpha$ varies approximately in between 0.4 and 0.8, robot $R_1$ is the best; and, for the case when $\alpha$ is greater than 0.8, robot $R_2$ appears as the best choice.

### 3.2.6 Discussion

The work bears significant managerial implication. Appropriate robot selection improves overall firm's efficiency and thereby enhances profitability. During robot selection, apart from objective criteria, a number of subjective criteria need to be evaluated simultaneously. As subjective criteria are ill-defined and vague in nature, their evaluation is based on linguistic assessment of the experts which is further transformed into appropriate fuzzy numbers. An integrated decision making module with the capability of simultaneously considering known (crisp) set of objective data as well as fuzzy database of subjective criteria has been proposed in this work. The PROMETHHE I and II method have been extended to work under fuzzy environment facilitating the said decision making in relation to a robot selection problem. Industries may adopt this decision support system for effective evaluation and selection of industrial robot. The same procedure may also be helpful to solve other decision making problems in industrial context.

In any real world decision making problem (ex. robot selection, in the present case), situation arises in which people have to consider objective as well as subjective data set. If the case is involved with objective data set only, traditional MCDM tools and techniques can solve the problem. If the case is associated with subjective data set only, fuzzy-based decision making approaches like Fuzzy-TOPSIS, Fuzzy-VIKOR, Fuzzy-MOORA may be applied. But the case, where objective as well as subjective data set need to be explored and analyzed simultaneously, it really becomes a tough job. As one looks into previous literature, it can be found that attempts have been made to use objective and subjective data, but in a different way. Here, objective data have been transformed into subjective (fuzzy) data and analyzed along with actual subjective data. On the other hand, subjective data have been defuzzified to get equivalent objective (crisp) score and analyzed along with actual objective data set. Literature seems rare in proposing such a decision making module which could simultaneously tackle both objective and subjective data without allowing towards changing their identity. This aspect has been articulated in this work.

### 3.2.7 Concluding Remarks

In this work, PROMETHHE approach has been extended to solve a robot selection (decision making) problem by considering objective as well as subjective criteria simultaneously. The procedural hierarchy of the proposed decision support system has been case empirically illustrated. Sensitivity analysis has also been performed to make a compatible balance (compromise) between objective factor measure and subjective factor measure. Finally, a compromise selection preference has been demonstrated by using Robot Selection Score (RSS). Sensitivity analysis plot reflects how variations of Decision-Makers' perception influence the most favorable choice. The proposed decision making module can also be applied in a variety of industrial decision making situations involving subjective as well as objective criteria evaluation.

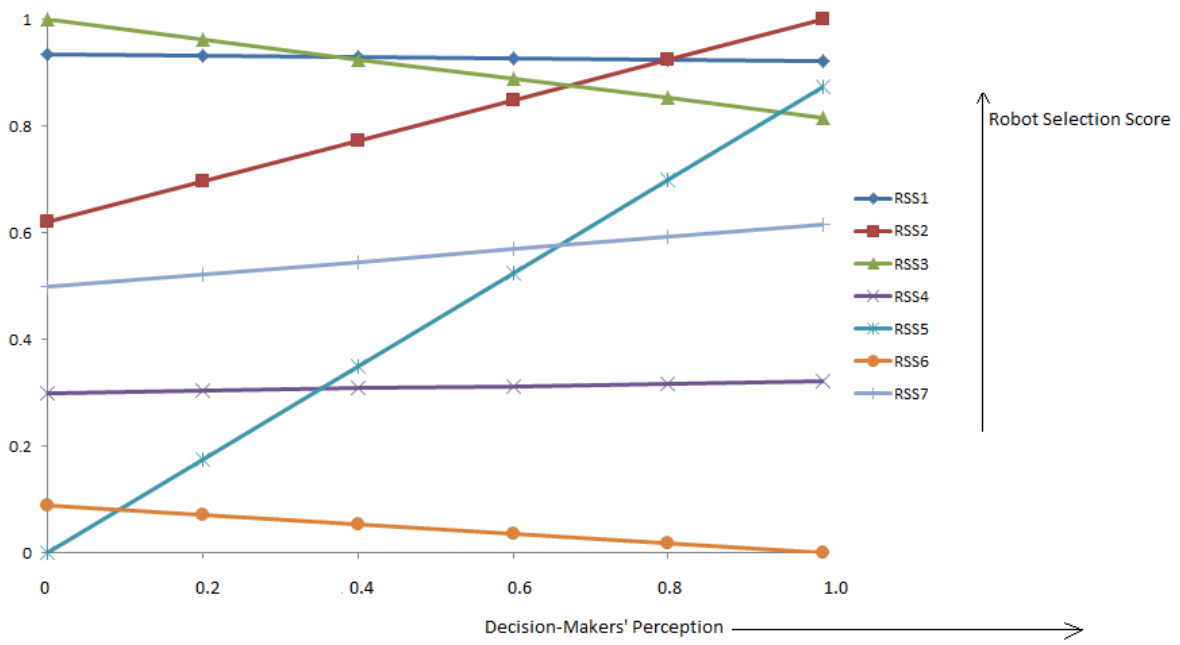


Fig. 3.6: Sensitivity analysis plot

Table 3.59: Linguistic scales and corresponding fuzzy representation for criteria weight and criteria rating with respect to alternatives

| Performance rating | Importance weight | Triangular fuzzy numbers |
|---|---|---|
| Very Poor (VP) | Very Low (VL) | (0, 0, 0.15) |
| Poor (P) | Low (L) | (0, 0.15, 0.3) |
| Medium Poor (MP) | Medium Low (ML) | (0.15, 0.3 0.5) |
| Medium (M) | Medium (M) | (0.3, 0.5, 0.65) |
| Medium Good (MG) | Medium High (MH) | (0.5, 0.65, 0.8) |
| Good (G) | High (H) | (0.65, 0.8, 1.0) |
| Very Good (VG) | Very High (VH) | (0.8, 1.0, 1.0) |

Table 3.60: Subjective weights for robot selection attributes as given by the DMs

| Criteria | Weights given by DMs | | | | Aggregated fuzzy weight |
|---|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 | |
| $C_1$ | VH | VH | H | H | (0.725,0.900,1.000) |
| $C_2$ | H | H | H | VH | (0.688, 0.850, 1.000) |
| $C_3$ | H | VH | VH | VH | (0.763, 0.950, 1.000) |
| $C_4$ | MH | H | H | H | (0.613, 0.763, 0.950) |
| $C_5$ | H | VH | VH | VH | (0.763, 0.950, 1.000) |
| $C_6$ | VH | VH | H | H | (0.725, 0.900, 1.000) |
| $C_7$ | H | VH | VH | H | (0.725, 0.900, 1.000) |
| $C_8$ | MH | MH | H | H | (0.575, 0.725, 0.900) |
| $C_9$ | H | MH | H | MH | (0.575, 0.725, 0.900) |
| $C_{10}$ | MH | MH | MH | MH | (0.500, 0.650, 0.800) |
| $C_{11}$ | H | MH | MH | H | (0.575, 0.725, 0.900) |
| $C_{12}$ | H | H | H | H | (0.650, 0.80, 1.000) |
| $C_{13}$ | MH | MH | H | H | (0.575, 0.725, 0.900) |

Table 3.61: Ratings for subjective attributes as given by the DMs and corresponding aggregated fuzzy representation

| Criteria | Alternatives | Ratings given by DMs | | | | Aggregated fuzzy rating |
|---|---|---|---|---|---|---|
| | | DM1 | DM2 | DM3 | DM4 | |
| $C_6$ | $R_1$ | VG | VG | G | G | (0.725, 0.900, 1.000) |
| $C_7$ | | G | MG | G | G | (0.613, 0.763, 0.950) |
| $C_8$ | | G | G | G | G | (0.650, 0.800, 1.000) |
| $C_9$ | | MG | G | G | G | (0.613, 0.763, 0.950) |
| $C_{10}$ | | G | G | G | G | (0.650, 0.800, 1.000) |
| $C_{11}$ | | MG | G | MG | G | (0.575, 0.725, 0.900) |
| $C_{12}$ | | G | G | G | G | (0.650, 0.800, 1.000) |
| $C_{13}$ | | MG | G | MG | MG | (0.538, 0.688, 0.850) |
| $C_6$ | $R_2$ | VG | G | G | G | (0.613, 0.763, 0.950) |
| $C_7$ | | VG | G | VG | G | (0.650, 0.813, ,0.950) |
| $C_8$ | | MG | MG | G | G | (0.575, 0.725, 0.900) |
| $C_9$ | | G | G | G | G | (0.650, 0.800, 1.000) |
| $C_{10}$ | | VG | G | VG | G | (0.725, 0.900, 1.000) |
| $C_{11}$ | | MG | MG | MG | MG | (0.500, 0.650, 0.800) |
| $C_{12}$ | | G | VG | VG | VG | (0.763, 0.950, 1.000) |
| $C_{13}$ | | G | G | G | G | (0.650, 0.800, 1.000) |
| $C_6$ | $R_3$ | M | M | MG | MG | (0.400, 0.575, 0.725) |
| $C_7$ | | M | M | MG | G | (0.438, 0.613, 0.775) |
| $C_8$ | | MG | G | G | G | (0.613, 0.763, 0.950) |
| $C_9$ | | G | G | MG | G | (0.613, 0.763, 0.950) |
| $C_{10}$ | | MG | G | MG | G | (0.575, 0.725, 0.900) |
| $C_{11}$ | | G | G | G | MG | (0.613, 0.763, 0.950) |
| $C_{12}$ | | MG | MG | MG | MG | (0.500, 0.650, 0.800) |
| $C_{13}$ | | G | G | G | MG | (0.613, 0.763, 0.950) |
| $C_6$ | $R_4$ | P | P | MP | MP | (0.075, 0.225, 0.400) |
| $C_7$ | | M | M | M | M | (0.300, 0.500, 0.650) |
| $C_8$ | | MP | P | M | M | (0.188, 0.363, 0.525) |
| $C_9$ | | M | M | M | M | (0.300, 0.500, 0.650) |
| $C_{10}$ | | P | MP | VP | MP | (0.113, 0.238, 0.400) |
| $C_{11}$ | | M | M | M | M | (0.300, 0.500, 0.650) |
| $C_{12}$ | | MP | MP | MP | M | (0.188, 0.350, 0.538) |
| $C_{13}$ | | M | M | M | M | (0.300, 0.500, 0.650) |

Table 3.61 (continued): Ratings for subjective attributes as given by the DMs and corresponding aggregated fuzzy representation

| Criteria | Alternatives | Ratings given by DMs | | | | Aggregated fuzzy rating |
|---|---|---|---|---|---|---|
| | | DM1 | DM2 | DM3 | DM4 | |
| $C_6$ | $R_5$ | G | MG | MG | MG | (0.538, 0.688, 0.850) |
| $C_7$ | | MG | MG | MG | MG | (0.500, 0.650, 0.800) |
| $C_8$ | | G | VG | G | G | (0.688, 0.850, 1.000) |
| $C_9$ | | MG | MG | G | G | (0.575, 0.725, 0.900) |
| $C_{10}$ | | G | G | G | G | (0.650, 0.800, 1.000) |
| $C_{11}$ | | MG | MG | MG | MG | (0.500, 0.650, 0.800) |
| $C_{12}$ | | G | G | G | G | (0.650, 0.800, 1.000) |
| $C_{13}$ | | MG | G | MG | G | (0.575, 0.725, 0.900) |
| $C_6$ | $R_6$ | P | P | P | P | (0.000, 0.150, 0.300) |
| $C_7$ | | VP | P | VP | P | (0.000, 0.075, 0.225) |
| $C_8$ | | P | P | P | P | (0.000, 0.150, 0.300) |
| $C_9$ | | VP | VP | VP | VP | (0.000, 0.000, 0.150) |
| $C_{10}$ | | P | P | P | VP | (0.000, 0.113, 0.263) |
| $C_{11}$ | | P | P | P | P | (0.000, 0.150, 0.300) |
| $C_{12}$ | | MP | MP | M | M | (0.225, 0.400, 0.575) |
| $C_{13}$ | | M | M | M | M | (0.300, 0.500, 0.650) |
| $C_6$ | $R_7$ | M | MG | MG | MG | (0.450, 0.613, 0.763) |
| $C_7$ | | M | MG | MG | M | (0.400, 0.575, 0.725) |
| $C_8$ | | M | M | M | M | (0.300, 0.500, 0.650) |
| $C_9$ | | MG | M | M | MG | (0.400, 0.575, 0.725) |
| $C_{10}$ | | MG | MG | M | MG | (0.450, 0.613, 0.763) |
| $C_{11}$ | | M | MG | MG | MG | (0.450, 0.613, 0.763) |
| $C_{12}$ | | MG | MG | MG | M | (0.450, 0.613, 0.763) |
| $C_{13}$ | | MG | M | MG | M | (0.400, 0.575, 0.725) |

Table 3.62: Objective data for robot selection

| Alternatives | LC (Kg), $C_1$ | RE (mm), $C_2$ | MTS (mm/sec), $C_3$ | MC (steps), $C_4$ | MR (mm), $C_5$ |
|---|---|---|---|---|---|
| R1 | 60 | 0.4 | 2540 | 500 | 990 |
| R2 | 6.35 | 0.15 | 1016 | 3000 | 1041 |
| R3 | 6.8 | 0.1 | 1727.2 | 1500 | 1676 |
| R4 | 10 | 0.2 | 1000 | 2000 | 965 |
| R5 | 2.5 | 0.1 | 560 | 500 | 915 |
| R6 | 4.5 | 0.08 | 1016 | 350 | 508 |
| R7 | 3 | 0.1 | 1778 | 1000 | 920 |

Table 3.63: Initial decision making matrix (objective data)

| Alter-natives | Objective criteria (in appropriate units) | | | | |
|---|---|---|---|---|---|
| | C1 | C2 | C3 | C4 | C5 |
| R1 | 60 | 0.4 | 2540 | 500 | 990 |
| R2 | 6.35 | 0.15 | 1016 | 3000 | 1041 |
| R3 | 6.8 | 0.1 | 1727.2 | 1500 | 1676 |
| R4 | 10 | 0.2 | 1000 | 2000 | 965 |
| R5 | 2.5 | 0.1 | 560 | 500 | 915 |
| R6 | 4.5 | 0.08 | 1016 | 350 | 508 |
| R7 | 3 | 0.1 | 1778 | 1000 | 920 |

Table 3.63 (continued): Initial decision making matrix (subjective data)

| Alter-natives | Subjective criteria | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 |
| R1 | (0.725,0.9001.000) | (0.613,0.7630.950) | (0.650,0.800,1.000) | (0.613,0.763,0.950) | (0.650,0.800,1.000) | (0.575,0.725,0.900) | (0.650,0.800,1.000) | (0.538,0.688,0.850) |
| R2 | (0.613,0.763,0.950) | (0.650,0.813,0.950) | (0.575,0.725,0.900) | (0.650,0.800,1.000) | (0.725,0.900,1.000) | (0.500,0.650,0.800) | (0.763,0.950,1.000) | (0.650,0.800,1.000) |
| R3 | (0.400,0.575,0.725) | (0.438,0.613,0.775 | (0.613,0.763,0.950) | (0.613,0.763,0.950) | (0.575,0.725,0.900) | (0.613,0.763,0.950) | (0.500,0.650,0.800) | (0.613,0.763,0.950) |
| R4 | (0.075,0.225,0.400) | (0.300,0.500,0.650) | (0.188,0.363,0.525) | (0.300,0.500,0.650) | (0.113,0.238,0.400) | (0.300,0.500,0.650) | (0.188,0.350,0.538) | (0.300,0.500,0.650) |
| R5 | (0.538,0.688,0.850) | (0.500,0.650,0.800) | (0.688,0.850,1.000) | (0.575,0.725,0.900) | (0.650,0.800,1.000) | (0.500,0.650,0.800) | (0.650,0.800,1.000) | (0.575,0.725,0.900) |
| R6 | (0.000,0.150,0.300) | (0.000,0.075,0.225) | (0.000,0.150,0.300) | (0.000,0.000,0.150) | (0.000,0.113,0.263) | (0.000,0.150,0.300) | (0.225,0.400,0.575) | (0.300,0.500,0.650) |
| R7 | (0.450,0.613,0.763) | (0.400,0.575,0.725) | (0.300,0.500,0.650) | (0.400,0.575,0.725) | (0.450,0.613,0.763) | (0.450,0.613,0.763) | (0.450,0.613,0.763) | (0.400,0.575,0.725) |

Table 3.64: Normalized decision matrix (objective data)

| Alternatives | Objective criteria (in appropriate units) | | | | |
|---|---|---|---|---|---|
| | C1 | C2 | C3 | C4 | C5 |
| R1 | 1 | 0.2 | 1 | 0.167 | 0.591 |
| R2 | 0.106 | 0.533 | 0.4 | 1 | 0.621 |
| R3 | 0.113 | 0.8 | 0.68 | 0.5 | 1 |
| R4 | 0.167 | 0.4 | 0.394 | 0.667 | 0.576 |
| R5 | 0.042 | 0.8 | 0.22 | 0.167 | 0.546 |
| R6 | 0.075 | 1 | 0.4 | 0.117 | 0.303 |
| R7 | 0.05 | 0.8 | 0.7 | 0.333 | 0.549 |

Table 3.64 (continued): Normalized decision matrix (subjective data)

| Alter-natives | Subjective criteria | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 |
| R1 | (0.725,0.900,1.000) | (0.645,0.803.1.000) | (0.650,0.800,1.000) | (0.613,0.763,0.950) | (0.650,0.800,1.000) | (0.605,0.763,0.947) | (0.650,0.800,1.000) | (0.538,0.688,0.850) |
| R2 | (0.613,0.763,0.950) | (0.684,0.855,1.000) | (0.575,0.725,0.900) | (0.650,0.800,1.000) | (0.725,0.900,1.000) | (0.526,0.684,0.842) | (0.763,0.950,1.000) | (0.650,0.800,1.000) |
| R3 | (0.400,0.575,0.725 | (0.461,0.645,0.816) | 0.613,0.763,0.950) | (0.613,0.763,0.950) | (0.575,0.725,0.900) | (0.645,0.803,1.000) | (0.500,0.650,0.800) | (0.613,0.763,0.950) |
| R4 | (0.075,0.225,0.400) | (0.316,0.526,0.684) | (0.188,0.363,0.525) | (0.300,0.500,0.650) | (0.113,0.238,0.400) | (0.316,0.526,0.684) | (0.188,0.350,0.538) | (0.300,0.500,0.650) |
| R5 | (0.538,0.688,0.850) | (0.526,0.684,0.842) | (0.688,0.850,1.000) | (0.575,0.725,0.900) | (0.650,0.800,1.000) | (0.526,0.684,0.842) | (0.650,0.800,1.000) | (0.575,0.725,0.900) |
| R6 | (0.000,0.150,0.300) | (0.000,0.079,0.237) | (0.000,0.150,0.300) | (0.000,0.000,0.150) | (0.000,0.113,0.263) | (0.000,0.158,0.316) | (0.225,0.400,0.575) | (0.300,0.500,0.650) |
| R7 | (0.450,0.613,0.763) | (0.421,0.605,0.763) | (0.300,0.500,0.650) | (0.400,0.575,0.725) | (0.450,0.613,0.763) | (0.474,0.645,0.803) | (0.450,0.613,0.763) | (0.400,0.575, 0.725) |

Table 3.65: Computation of preference function [ $P_j(a,b)$ when $j$ is objective criterion and $\tilde{P}_j(a,b)$ when $j$ is subjective criterion]

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ | $C_{10}$ | $C_{11}$ | $C_{12}$ | $C_{13}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $R_1, R_1$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_1, R_2$ | 0.894 | 0.000 | 0.600 | 0.000 | 0.000 | (0.113,0.138,0.050) | (0.000,0.000,0.000) | (0.075,0.075,0.100) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.079,0.079,0.105) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_1,R_3$ | 0.887 | 0.000 | 0.320 | 0.000 | 0.000 | (0.325,0.325,0.275) | (0.184,0.158,0.184) | (0.038,0.038,0.050) | (0.000,0.000,0.000) | (0.075,0.075,0.100) | (0.000,0.000,0.000) | (0.150,0.150,0.200) | (0.000,0.000,0.000) |
| $R_1, R_4$ | 0.833 | 0.000 | 0.606 | 0.000 | 0.015 | (0.650,0.675,0.600) | (0.329,0.276,0.316) | (0.463,0.438,0.475) | (0.313,0.263,0.300) | (0.538,0.563,0.600) | (0.289,0.237,0.263) | (0.463,0.450,0.463) | (0.238,0.188,0.200) |
| $R_1, R_5$ | 0.958 | 0.000 | 0.780 | 0.000 | 0.045 | (0.188,0.213,0.150) | (0.118,0.118,0.158) | (0.000,0.000,0.000) | (0.038,0.037,0.050) | (0.000,0.000,0.000) | (0.079,0.079,0.105) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_1, R_6$ | 0.925 | 0.000 | 0.600 | 0.050 | 0.288 | (0.725,0.750,0.700) | (0.645,0.724,0.763) | (0.650,0.650,0.700) | (0.613,0.763,0.800) | (0.650,0.688,0.738) | (0.605,0.605,0.632) | (0.425,0.400,0.425) | (0.238,0.188,0.200) |
| $R_1, R_7$ | 0.950 | 0.000 | 0.300 | 0.000 | 0.042 | (0.275,0.288,0.238) | (0.224,0.197,0.237) | (0.350,0.300,0.350) | (0.213,0.188,0.225) | (0.200,0.188,0.238) | (0.132,0.118,0.145) | (0.200,0.188,0.238) | (0.138,0.113,0.125) |
| $R_2, R_1$ | 0.000 | 0.333 | 0.000 | 0.833 | 0.030 | (0.000,0.000,0.000) | (0.039,0.053,0.000) | (0.000,0.000,0.000) | (0.038,0.038,0.050) | (0.075,0.100,0.000) | (0.000,0.000,0.000) | (0.113,0.150,0.000) | (0.113,0.113,0.150) |
| $R_2, R_2$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_2, R_3$ | 0.000 | 0.000 | 0.000 | 0.500 | 0.000 | (0.213,0.188,0.225) | (0.224,0.211,0.184) | (0.000,0.000,0.000) | (0.038,0.038,0.050) | (0.150,0.175,0.100) | (0.000,0.000,0.000) | (0.263,0.300,0.200) | (0.038,0.038,0.050) |
| $R_2, R_4$ | 0.000 | 0.133 | 0.006 | 0.333 | 0.045 | (0.538,0.538,0.550) | (0.368,0.329,0.316) | (0.388,0.363,0.375) | (0.350,0.300,0.350) | (0.613,0.663,0.600) | (0.211,0.158,0.158) | (0.575,0.600,0.463) | (0.350,0.300,0.350) |
| $R_2, R_5$ | 0.064 | 0.000 | 0.180 | 0.833 | 0.075 | (0.075,0.075,0.100) | (0.158,0.171,0.158) | (0.000,0.000,0.000) | (0.075,0.075,0.100) | (0.075,0.100,0.000) | (0.000,0.000,0.000) | (0.113,0.150,0.000) | (0.075,0.075,0.100) |
| $R_2, R_6$ | 0.031 | 0.000 | 0.000 | 0.883 | 0.318 | (0.613,0.613,0.650) | (0.684,0.776,0.763) | (0.575,0.575,0.600) | (0.650,0.800,0.850) | (0.725,0.788,0.738) | (0.526,0.526,0.526) | (0.538,0.550,0.425) | (0.350,0.300,0.350) |
| $R_2, R_7$ | 0.056 | 0.000 | 0.000 | 0.667 | 0.072 | (0.163,0.150,0.188) | (0.263,0.250,0.237) | (0.275,0.225,0.250) | (0.250,0.225,0.275) | (0.275,0.288,0.238) | (0.053,0.039,0.039) | (0.313,0.338,0.238) | (0.250,0.225,0.275) |
| $R_3, R_1$ | 0.000 | 0.600 | 0.000 | 0.333 | 0.409 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.039,0.039,0.053) | (0.000,0.000,0.000) | (0.075,0.075,0.100) |
| $R_3, R_2$ | 0.008 | 0.267 | 0.280 | 0.000 | 0.379 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.038,0.037,0.050) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.118,0.118,0.158) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_3, R_3$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_3, R_4$ | 0.000 | 0.400 | 0.286 | 0.000 | 0.424 | (0.325,0.350,0.325) | (0.145,0.118,0.132) | (0.425,0.400,0.425) | (0.313,0.263,0.300) | (0.463,0.488,0.500) | (0.329,0.276,0.316) | (0.313,0.300,0.263) | (0.313,0.263,0.300) |
| $R_3, R_5$ | 0.072 | 0.000 | 0.460 | 0.333 | 0.454 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.038,0.037,0.050) | (0.000,0.000,0.000) | (0.118,0.118,0.158) | (0.000,0.000,0.000) | (0.038,0.038,0.050) |
| $R_3, R_6$ | 0.038 | 0.000 | 0.280 | 0.383 | 0.697 | (0.400,0.425,0.425) | (0.461,0.566,0.579) | (0.613,0.613,0.650) | (0.613,0.763,0.800) | (0.575,0.613,0.638) | (0.645,0.645,0.684) | (0.275,0.250,0.225) | (0.313,0.263,0.300) |
| $R_3, R_7$ | 0.063 | 0.000 | 0.000 | 0.167 | 0.451 | (0.000,0.000,0.000) | (0.039,0.039,0.053) | (0.313,0.263,0.300) | (0.213,0.188,0.225) | (0.125,0.113,0.138) | (0.171,0.158,0.197) | (0.050,0.038,0.038) | (0.213,0.188,0.225) |
| $R_4, R_1$ | 0.000 | 0.200 | 0.000 | 0.500 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.0000.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_4, R_2$ | 0.061 | 0.000 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_4, R_3$ | 0.053 | 0.000 | 0.000 | 0.167 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.0000.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) ) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_4, R_4$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.0000.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) ) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_4, R_5$ | 0.125 | 0.000 | 0.173 | 0.500 | 0.030 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.0000.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |

Table 3.65 (continued): Computation of preference function [ $P_j\left(a,b\right)$ when $j$ is objective criterion and $\tilde{P}_j\left(a,b\right)$ when $j$ is subjective criterion]

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ | $C_{10}$ | $C_{11}$ | $C_{12}$ | $C_{13}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $R_4$, $R_6$ | 0.092 | 0.000 | 0.000 | 0.550 | 0.273 | (0.075,0.075,0.100) | (0.316,.447,0.447) | (0.188,0.213,0.225) | (0.300,0.500,0.500) | (0.113,0.125,0.138) | (0.316,0.368,0.368) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_4$, $R_7$ | 0.117 | 0.000 | 0.000 | 0.333 | 0.027 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_5$, $R_1$ | 0.000 | 0.600 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.038,0.050,0.000 | (0.000,0.000,0.000) | (0.000,0.0000.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.038,0.038,0.050) |
| $R_5$, $R_2$ | 0.000 | 0.267 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.113,0.125,0.100) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_5$, $R_3$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | (0.138,0.113,0.125) | (0.066,0.039,0.026) | (0.075,0.088,0.050) | (0.000,0.000,0.000) | (0.075,0.075,0.100) | (0.000,0.000,0.000) | (0.150,0.150,0.200) | (0.000,0.000,0.000) |
| $R_5$, $R_4$ | 0.000 | 0.400 | 0.000 | 0.000 | 0.000 | (0.463,0.463,0.450) | (0.211,0.158,0.158) | (0.500,0.488,0.475) | (0.275,0.225,0.250) | (0.538,0.563,0.600) | (0.211,0.158,0.158) | (0.463,0.450,0.463) | (0.275,0.225,0.250) |
| $R_5$, $R_5$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_5$, $R_6$ | 0.000 | 0.000 | 0.000 | 0.050 | 0.243 | (0.538,0.538,0.550) | (0.526,0.605,0.605) | (0.688,0.700,0.700) | (0.575,0.725,0.750) | (0.650,0.688,0.738) | (0.526,0.526,0.526) | (0.425,0.400,0.425) | (0.275,0.225,0.250) |
| $R_5$, $R_7$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | (0.088,0.075,0.088) | (0.105,0.079,0.079) | (0.388,0.350,0.350) | (0.175,0.150,0.175) | (0.200,0.188,0.238) | (0.053,0.039,0.039) | (0.200,0.188,0.238) | (0.175,0.1500.175) |
| $R_6$, $R_1$ | 0.000 | 0.800 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_6$, $R_2$ | 0.000 | 0.467 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.0000.000,0.000) |
| $R_6$, $R_3$ | 0.000 | 0.200 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_6$, $R_4$ | 0.000 | 0.600 | 0.006 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.038,0.050,0.038) | (0.000,0.000,0.000) |
| $R_6$, $R_5$ | 0.033 | 0.200 | 0.180 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_6$, $R_6$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_6$, $R_7$ | 0.025 | 0.200 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_7$, $R_1$ | 0.000 | 0.600 | 0.000 | 0.167 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000)v | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_7$, $R_2$ | 0.000 | 0.267 | 0.300 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_7$, $R_3$ | 0.000 | 0.000 | 0.020 | 0.000 | 0.000 | (0.050,0.038,0.037) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.0000.000) |
| $R_7$, $R_4$ | 0.000 | 0.400 | 0.306 | 0.000 | 0.000 | (0.375,0.388,0.363) | (0.105,0.079,0.079) | (0.113,0.138,0.125) | (0.100,0.075,0.075) | (0.338,0.375,0.363) | (0.158,0.118,0.118) | (0.263,0.263,0.225) | (0.100,0.075,0.075) |
| $R_7$, $R_5$ | 0.008 | 0.000 | 0.480 | 0.167 | 0.003 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_7$, $R_6$ | 0.000 | 0.000 | 0.300 | 0.217 | 0.246 | (0.450,0.463,0.463) | (0.421,0.526,0.526) | (0.300,0.350,0.350) | (0.400,0.575,0.575) | (0.450,0.500,0.500) | (0.474,0.487,0.487) | (0.225,0.213,0.188) | (0.100,0.075,0.075) |
| $R_7$, $R_7$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |

Table 3.66: Computation of multi-criteria preference index $\tilde{\pi}(a,b)$

| | $R_1$ | $R_2$ | $R_3$ | $R_4$ | $R_5$ | $R_6$ | $R_7$ |
|---|---|---|---|---|---|---|---|
| $R_1$ | (0.000,0.000,0.000) | (0.103,0.152,0.210) | (0.115,0.167,0.226) | (0.259,0.365,0.487) | (0.131,0.192,0.269) | (0.349,0.525,0.733) | (0.165,0.234,0.336) |
| $R_2$ | (0.082,0.116,0.158) | (0.000,0.000,0.000) | (0.077,0.105,0.139) | (0.206,0.281,0.362) | (0.093,0.131,0.183) | (0.309,0.462,0.642) | (0.136,0.186,0.261) |
| $R_3$ | (0.081,0.117,0.176) | (0.063,0.092,0.141) | (0.000,0.000,0.000) | (0.200,0.279,0.382) | (0.086,0.126,0.190) | (0.280,0.427,0.612) | (0.093,0.129,0.203) |
| $R_4$ | (0.036,0.052,0.080) | (0.004,0.005,0.007) | (0.011,0.017,0.025) | (0.000,0.000,0.000) | (0.045,0.065,0.095) | (0.116,0.201,0.308) | (0.025,0.036,0.054) |
| $R_5$ | (0.037,0.054,0.076) | (0.020,0.030,0.042) | (0.027,0.038,0.047) | (0.174,0.240,0.309) | (0.000,0.000,0.000) | (0.235,0.358,0.494) | (0.068,0.093,0.130) |
| $R_6$ | (0.045,0.064,0.095) | (0.026,0.038,0.055) | (0.011,0.016,0.024) | (0.036,0.053,0.076) | (0.024,0.035,0.049) | (0.000,0.000,0.000) | (0.013,0.018,0.027) |
| $R_7$ | (0.042,0.060,0.090) | (0.033,0.048,0.067) | (0.004,0.005,0.007) | (0.125,0.175,0.215) | (0.039,0.056,0.077) | (0.193,0.305,0.419) | (0.000,0.000,0.000) |

Table 3.67: Outgoing/leaving flows, incoming/entering flows and net flow values for different robot alternatives

| Alternatives | $\tilde{\phi}^{+}(a)$ | $\phi^{+}(a)$ | $\tilde{\phi}^{-}(a)$ | $\phi^{-}(a)$ | $\phi(a)$ | Ranking order |
|---|---|---|---|---|---|---|
| $R_1$ | (1.122,1.636,2.261) | 1.673 | (0.322,0.464,0.675) | 0.487 | 1.186 | 1 |
| $R_2$ | (0.903,1.282,1.746) | 1.310 | (0.250,0.366,0.522) | 0.379 | 0.931 | 2 |
| $R_3$ | (0.804,1.170,1.702) | 1.225 | (0.246,0.348,0.468) | 0.354 | 0.871 | 3 |
| $R_4$ | (0.237,0.377,0.569) | 0.394 | (1.000,1.392,1.831) | 1.408 | -1.013 | 6 |
| $R_5$ | (0.562,0.813,1.099) | 0.825 | (0.417,0.605,0.863) | 0.628 | 0.196 | 4 |
| $R_6$ | (0.154,0.224,0.325) | 0.235 | (1.482,2.279,3.207) | 2.323 | -2.088 | 7 |
| $R_7$ | (0.436,0.650,0.874) | 0.653 | (0.500,0.697,1.012) | 0.736 | -0.083 | 5 |

Table 3.68: Multi-criteria preference index $\tilde{\pi}(a,b)$ between two alternatives $a$ and $b$ (considering objective criteria only i.e. $C_1$ to $C_5$)

| | $R_1$ | $R_2$ | $R_3$ | $R_4$ | $R_5$ | $R_6$ | $R_7$ |
|---|---|---|---|---|---|---|---|
| $R_1$ | (0.000,0.000,0.000) | (0.223,0.312,0.421) | (0.179,0.250,0.340) | (0.218,0.304,0.410) | (0.267,0.373,0.502) | (0.278,0.388,0.524) | (0.192,0.267,0.364) |
| $R_2$ | (0.154,0.215,0.325) | (0.000,0.000,0.000) | (0.062,0.086,0.134) | (0.068,0.094,0.141) | (0.152,0.212,0.313) | (0.163,0.227,0.335) | (0.102,0.142,0.214) |
| $R_3$ | (0.188,0.261,0.374) | (0.140,0.195,0.263) | (0.000,0.000,0.000) | (0.165,0.230,0.313) | (0.193,0.269,0.367) | (0.204,0.284,0.389) | (0.099,0.139,0.190) |
| $R_4$ | (0.090,0.125,0.190) | (0.009,0.012,0.017) | (0.028,0.040,0.060) | (0.000,0.000,0.000) | (0.112,0.156,0.226) | (0.124,0.172,0.250) | (0.063,0.087,0.130) |
| $R_5$ | (0.083,0.116,0.169) | (0.037,0.051,0.075) | (0.000,0.000,0.000) | (0.056,0.077,0.113) | (0.000,0.000,0.000) | (0.044,0.061,0.082) | (0.000,0.000,0.000) |
| $R_6$ | (0.111,0.154,0.225) | (0.065,0.090,0.131) | (0.028,0.039,0.056) | (0.084,0.117,0.171) | (0.060,0.084,0.116) | (0.000,0.000,0.000) | (0.031,0.044,0.063) |
| $R_7$ | (0.104,0.144,0.214) | (0.083,0.116,0.160) | (0.003,0.004,0.006) | (0.103,0.143,0.199) | (0.096,0.134,0.183) | (0.111,0.155,0.212) | (0.000,0.000,0.000 |

Table 3.69: Net flow values of different robot alternatives for objective criteria only

| Robots | $\tilde{\phi}^+(a)$ | $\phi^+(a)$ | $\tilde{\phi}^-(a)$ | $\phi^-(a)$ | $\phi(a)$ |
|---|---|---|---|---|---|
| $R_1$ | (1.358,1.893,2.561) | 1.937 | (0.730,1.015,1.497) | 1.081 | 0.857 |
| $R_2$ | (0.701,0.977,1.463) | 1.047 | (0.557,0.776,1.067) | 0.800 | 0.247 |
| $R_3$ | (0.988,1.378,1.894) | 1.420 | (0.300,0.419,0.595) | 0.438 | 0.982 |
| $R_4$ | (0.425,0.592,0.873) | 0.630 | (0.693,0.965,1.346) | 1.002 | -0.372 |
| $R_5$ | (0.220,0.305,0.439) | 0.321 | (0.880,1.228,1.707) | 1.272 | -0.951 |
| $R_6$ | (0.380,0.527,0.764) | 0.557 | (0.923,1.289,1.791) | 1.334 | -0.777 |
| $R_7$ | `(0.500,0.697,0.972) | 0.723 | (0.487,0.679,0.961) | 0.709 | 0.014 |

Notes: Outgoing/leaving flows, incoming/entering flows and net flow values for different robot alternatives (considering objective criteria only i.e. $C_1$ to $C_5$)

Table 3.70: Preference index for subjective criteria

| | $R_1$ | $R_2$ | $R_3$ | $R_4$ | $R_5$ | $R_6$ | $R_7$ |
|---|---|---|---|---|---|---|---|
| $R_1$ | (0.000,0.000,0.000) | (0.023,0.038,0.048) | (0.071,0.103,0.160) | (0.274,0.390,0.607) | (0.039,0.062,0.091) | (0.379,0.600,0.934) | (0.145,0.200,0.339) |
| $R_2$ | (0.030,0.550,0.037) | (0.000,0.000,0.000) | (0.082,0.125,0.159) | (0.282,0.407,0.595) | (0.049,0.084,0.089) | (0.387,0.618,0.923) | (0.152,0.217,0.328) |
| $R_3$ | (0.009,0.013,0.028) | (0.012,0.018,0.038) | (0.000,0.000,0.000) | (0.212,0.301,0.475) | (0.015,0.023,0.047) | (0.317,0.511,0.802) | (0.087,0.116,0.215) |
| $R_4$ | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.108,0.217,0.335) | (0.000,0.000,0.000) |
| $R_5$ | (0.006,0.010,0.009) | (0.009,0.015,0.018) | (0.044,0.060,0.097) | (0.241,0.338,0.524) | (0.000,0.000,0.000) | (0.346,0.548,0.852) | (0.111,0.148,0.257) |
| $R_6$ | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.003,0.007,0.008) | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.000,0.000,0.000) |
| $R_7$ | (0.000,0.000,0.000) | (0.000,0.000,0.000) | (0.005,0.005,0.008) | (0.129,0.190,0.267) | (0.000,0.000,0.000) | (0.234,0.400,0.595) | (0.000,0.000, 0.000) |

Notes: Multi-criteria preference index $\tilde{\pi}(a,b)$ between two alternatives $a$ and $b$ (considering subjective criteria only i.e. $C_6$ to $C_{13}$)

Table 3.71: Net flow values of different robot alternatives for subjective criteria only

| Robots | $\tilde{\phi}^{+}(a)$ | $\phi^{+}(a)$ | $\tilde{\phi}^{-}(a)$ | $\phi^{-}(a)$ | $\phi(a)$ |
|---|---|---|---|---|---|
| $R_1$ | (0.931,1.393,2.179) | 1.501 | (0.045,0.574,0.074) | 0.231 | 1.270 |
| $R_2$ | (0.982,2.000,2.132) | 1.704 | (0.044,0.071,0.104) | 0.073 | 1.631 |
| $R_3$ | (0.652,0.983,1.605) | 1.080 | (0.202,0.293,0.424) | 0.306 | 0.774 |
| $R_4$ | (0.108,0.217,0.335) | 0.220 | (1.141,1.632,2.476) | 1.750 | -1.530 |
| $R_5$ | (0.757,1.119,1.758) | 1.211 | (0.103,0.169,0.228) | 0.167 | 1.045 |
| $R_6$ | (0.003,0.007,0.008) | 0.006 | (1.771,2.895,4.440) | 3.036 | -3.030 |
| $R_7$ | (0.369,0.596,0.870) | 0.612 | (0.495,0.681,1.139) | 0.772 | -0.160 |

Notes: Outgoing/leaving flows, incoming/entering flows and net flow values for different robot alternatives (Considering subjective criteria only i.e. $C_6$ to $C_{13}$)

Table 3.72: Computation of Robot selection scores (RSSs) (combining two different selections)

| Alternatives | $\phi(a)$ (considering objective criteria) | OFM (normalized $\phi(a)$) | Ranking order (Considering objective criteria only) | $\phi(a)$ (considering subjective criteria) | SFM (normalized $\phi(a)$) | Ranking order (Considering subjective criteria only) |
|---|---|---|---|---|---|---|
| $R_1$ | 0.857 | 0.935 | 2 | 1.270 | 0.923 | 2 |
| $R_2$ | 0.247 | 0.620 | 3 | 1.631 | 1.000 | 1 |
| $R_3$ | 0.982 | 1.000 | 1 | 0.774 | 0.816 | 4 |
| $R_4$ | -0.372 | 0.300 | 5 | -1.530 | 0.322 | 6 |
| $R_5$ | -0.951 | 0.000 | 7 | 1.045 | 0.874 | 3 |
| $R_6$ | -0.777 | 0.090 | 6 | -3.030 | 0.000 | 7 |
| $R_7$ | 0.014 | 0.499 | 4 | -0.160 | 0.616 | 5 |

# Chapter 4

# A New TODIM-Based Decision Support Framework for G-Resilient Supplier Selection in Fuzzy Environment

## 4.1 Coverage

A novel decision support framework has been proposed herein to solve supplier selection problems by considering green as well as resiliency criteria, simultaneously. In this work subjectivity of evaluation criteria has been tackled by exploring fuzzy set theory. A dominance based approach has been conceptualized which is basically a simplified version of TODIM. Application potential of the proposed dominance based fuzzy decision making approach has been compared to that of fuzzy-TOPSIS, fuzzy-VIKOR and also fuzzy-TODIM. The concept of a unique performance index, i.e. 'g-resilient' index has been introduced here to help in assessing suppliers' performance and thereby selecting the best candidate. The work has also been extended to identify the areas in which suppliers are lagging; and seek further improvement towards g-resilient suppliers' performance to be boosted up to the desired level.

## 4.2 Background and Problem Statement

Managing the movement of goods (or products) from one point to another, subjected to certain constraints, is well acknowledged as Supply Chain Management (SCM). In a broader sense, ensuring the synchronization between various network activities from the beginning to the destination is referred as supply chain management. In traditional supply chain activities, huge industrial wastes resulted in high level of environmental pollution. In order to save environment and also the Earth, green concepts were introduced; traditional supply chain was reoriented as Green Supply Chain (GSC). The primary motivation for consideration of Green Supply Chain Management (GSCM) is to diminish environmental deterioration throughout the product life cycle. GSCM intends to eliminate various industrial wastes including hazardous chemical, emissions, energy and solid waste along every network activities such as product design, material resourcing and selection, manufacturing process, delivery of final product and end-of-life management of the product (Chin et al., 2015; Rao, 2006; Srivastava, 2007). Supply chain performance can be enhanced by adopting green practices which in turn results better cost saving and profitability. Adding the 'green' component to supply chain management involves addressing the influence and relationships between supply chain management and natural environment (Srivastava, 2007).

It is well understood that a firm cannot survive for long term without supplier's contribution as they are the dealer who supply necessary goods and services that the firm cannot self-produce (Kuo et al., 2010). Selection and management of appropriate supplier is the key to acquire desired level of quality products at the reasonable price with on-time delivery. Thus, to support GSCM, supplier selection should emphasize on supplier's ability to adopt green concepts like green image, green competencies, green packaging, environmental management and capability of preventing environmental pollution. However, (Zhu et al., 2008) stated that the green paradigm is concerned with environmental risks and environmental impact reduction only and does not consider the effects of disturbances on the system. In order to handle such system disturbances, (Christopher and Peck, 2004) introduced the concept of resilient supply chain and highlighted resilient paradigm which focused on the supply chain ability to recover to the desired state after a disruption occurs. Disruption is a low probability high intensity event (LPHI) which may cause system unbalance (turbulence) for a long term. Therefore, preparation for sustaining in disruption situations should also be considered as a critical strategic issue in supplier selection process. Thus, proactive arrangement for these sorts of happenings should be a priority for supply chain managers (Haldar et al., 2014).

Resiliency is an adaptive control term where firms prepare themselves to cope up with any unexpected event or demand by assuring the continuity of the operation at the best possible rate. It is also described as the capacity of a system to attain its original state after disruption is incurred. According to (Fiksel, 2006), resiliency refers to a firm's capacity to survive, adapt and grow in the face of change and uncertainty. Tierney and Bruneau (2007) explored the concept of a resilience triangle (as shown in Fig. 4.1) that was emerged from the disaster research and characterized the loss of functionality from damage and risk. The depth of the triangle represents the disruption severity; more specifically it is the severity or magnitude of loss or damage. The length of the triangle shows the recovery time that is the time taken for the restoration; it is also known as the damping time. Reduced size of triangle shows a strong resiliency in the company's supply chain. Therefore, the resilience triangle should be minimized at the best possible way. Actions, behavior, and properties of companies and networks can contribute for reducing the area of the resilience triangle.

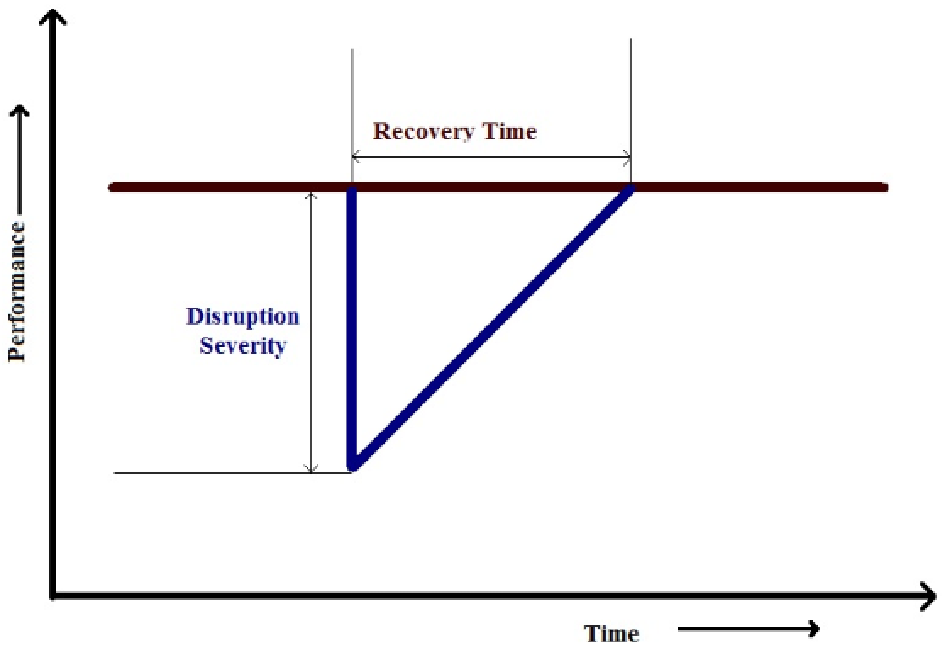


Fig. 4.1: Resilience triangle

Haimes (2006) reported that resilience approaches are having two broad intentions (i) to provide a recovery tool for the system that has been previously disturbed, within an acceptable time range and at a standard cost, and (ii) to provide control for the disturbances on the system by reducing the adverse effect which may cause a possible interruption. As it is evident from the literature that resiliency provides a strong recovery tool and a better control on disruption; whereas, adaptation to green practices offers reduced waste thereby protecting the environment. Therefore, in addition to traditional supplier selection criteria, a firm's supplier selection should take care of suppliers' resiliency strategy along with green consciousness as well. Awasthi et al. (2010) applied fuzzy-TOPSIS for evaluating environmental performance of suppliers. Shaik and Abdul-Kader (2011) presented a generic framework integrating environmental and social criteria leading to a comprehensive selection process of green suppliers. Çifçi and Büyüközkan (2011) presented a decision support framework based on group decision making (GDM) and fuzzy Analytical Hierarchy Process (FAHP) for evaluating and selecting green suppliers. Datta et al. (2012) reported a methodology for the evaluation of suppliers' environmental performances. Bakeshlou et al. (2014) developed a multi-objective fuzzy linear programming model for a Green Supplier Selection (GSS) problem.

Banaeian et al. (2015) formulated an integrated framework for deciding about the green supplier selection criteria in food supply chain in consideration with single and multiple sourcing of supplier selection. Freeman and Chen (2015) focused on development of a green supplier selection model using an index system based on a combination of traditional supplier and environmental supplier selection criteria for the case company— a Chinese-based electronic machinery manufacturer. The decision model explored AHP and the TOPSIS. Hashemi et al. (2015) considered both economic and environmental criteria and thereby proposed a comprehensive green supplier selection model. The analytic network process was used to deal with the interdependencies among the criteria, and the modified grey relational analysis was applied to better address the uncertainties inherent in supplier selection decisions.

Aforesaid section represents outlines of past research on green supplier selection. The following section highlights few researches carried out so far on various issues of resilient supplier selection. Haldar et al. (2012) developed a quantitative approach for supplier selection under a disaster environment. In another reporting, Haldar et al. (2014) provided an approach for strategic supplier selection, under a fuzzy environment, in a disaster scenario. This paper presented an integrated fuzzy group decision making approach based on a fuzzy technique for TOPSIS to rank the suppliers of a manufacturing system. Chen et al. (2014) sought to verify the criteria for selecting suppliers by using global performance measurements to identify optimal supply resources and locations in an uncertain disaster environment. Owing to the increased necessity of integrating green and resilient supply chain philosophies in recent times, the efficient supplier selection to support g-resilient supply chain management appears to be a challenging research agenda in supply chain literature. Apart from considering traditional supplier selection criteria (cost, quality, delivery, and service), green and resiliency criteria need to be assessed simultaneously for evaluating suppliers' performance. Literature is very limited in applying integrated decision support tools on the deployment of green and resilient strategies simultaneously, particularly for the supplier selection problem. Supplier selection process may include quantitative/qualitative information (or combination of both); to handle the situation, past researcher developed numerous decision making tools and techniques to provide realistic solutions.

Quantitative information or criteria can be evaluated by applying traditional Multi-Criteria Decision Making (MCDM) methodologies; whereas, qualitative criteria information were analyzed in fuzzy/grey environment. In this context, a novel decision support framework has been delineated herein to facilitate g-resilient supplier selection in fuzzy environment. Application potential of the proposed decision support module has been compared to that of fuzzy-TOPSIS (Junior et al., 2014; Mokhtarian, 2015; Sang et al., 2015), fuzzy-VIKOR (Pourebrahim et al., 2014; Liu et al., 2015) as well as fuzzy-TODIM (Krohling and deSouza, 2012). A unique g-resilient index has also been computed for individual supplier alternatives; based on which suppliers have been ranked and the best supplier has been selected. In addition to that, the work has been extended to identify ill-performing areas in which suppliers should pay attention in future to boost up their g-resilient performance up to the desired extent.

The objectives of the current work have been highlighted below.

i. To propose a systematic and logical decision support framework to facilitate g-resilient supplier selection. The proposed framework is basically a simplified version of TODIM. The novelty of this approach is to eliminate complex procedural steps of TODIM.
ii. To cope up with ill-defined and vague evaluation criteria (in regards of green as well as resiliency performance), the proposed decision support framework has been formulated to work under fuzzy environment.
iii. To validate suppliers ranking order obtained herewith by comparing the same to that of fuzzy-TOPSIS as well as fuzzy-VIKOR, and also fuzzy-TODIM.
iv. To evaluate a unique performance index called “g-resilient” index for individual supplier alternatives; and thereby to obtain the preference ranking order.

v. To identify ill-performing areas of individual supplier alternatives which are required to be improved in future to boost up supplier's g-resilient performance.

## 4.3 Proposed Decision Support Framework: Theoretical Basis

The decision support system proposed herein is the simplified version of TODIM (Tomada de Decisi´on Inerativa Multicritero). TODIM (an acronym in Portuguese of interactive and multi-criteria decision making) method makes use of a global measurement of value calculable by the application of the paradigm of prospect theory (Kahneman and Tversky, 1979). The method is based on a description, proved by empirical evidence, of how people effectively make decisions in the face of risk. The shape of the value function of TODIM appears the same as the gain/loss function of prospect theory (Gomes and Rangel, 2009; Tosun and Akyüz, 2015). In the proposed decision support system, the dominance is measured but not transformed into gain/loss function (as in TODIM) or preference function (as in PROMETHEE, i.e. Preference Ranking Organization Method for Enrichment Evaluations) (Gupta et al., 2012; Avikal et al., 2014; Elevli, 2014; Motlagh et al., 2015; Chen, 2014; Peng et al., 2014; Kabir and Sumi, 2014). In this approach, whilst two alternatives are compared with respect to a particular criterion; if the difference between the evaluation measures becomes positive; that means, the first alternative is dominating the second one and hence the dominance measure is assumed to be positive. In the reverse case, if the difference between evaluation measures appears negative; it means, the first alternative is dominated by the second one. Therefore, the dominance extent for the first alternative assumes a negative value. The dominance between two alternatives (with respect to a particular criterion) is computed to obtain partial matrices of dominance. The global matrices of dominance are then computed for the candidate alternatives; based on which a global index measure is obtained to facilitate final ranking. The proposed decision making pathways outlined herein surely avoids computational complexity of TODIM as well as PROMETHEE. Moreover, these procedural steps are indeed borrowed from the TODIM method, but without the use of the prospect theory-inspired value function which is the most important contribution as compared to the TODIM approach.

As a matter of fact, some ideas of TODIM are much more present in the proposed approach than these of PROMETHEE; since, it does not deal with outranking relations which are essential in PROMETHEE methods as in other methods of the so called French School of Multi-Criteria Decision Making (MCDM). Through the proposed Decision Support System (DSS) has been conceptualized in light of TODIM, the same has been attributed to operate under fuzzy environment. Hence, at this stage, preliminaries of fuzzy set theory, fuzzy mathematics needs to be understood in detail. These aspects could be well retrieved from (Chen et al., 1997; Chen, 2000; Chen and Chen, 2007; Kauffman and Gupta, 1991; Zimmermann, 1991).

The procedural steps of the decision support system proposed herein have been summarized below.

***Step 1:*** Arrange the decision making group, set of alternatives and evaluation criteria.

Assume $m$ possible alternatives: $A=\{A_1, A_2, ..., A_m\}$,

$n$ evaluation criteria $\{C_1, C_2, ...., C_n\}$, and

$K$ decision-makers: $E=\{D_1, D_2, ...., D_K\}$

Also, $i=1,2,...,m;\ j=1,2,...,n$ and $k=1,2,...,K$.

***Step 2:*** Construction of the decision matrix for each of the decision-makers in relation to appropriateness rating $\left(\tilde{x}_{ij}^k\right)$ of alternatives with respect to criteria; and also obtain decision-makers' judgment in regards of weight of the criteria $\left(\tilde{w}_j^k\right)$.

(assuming trapezoidal fuzzy number)

$$\tilde{x}_{ij}^k=\left(\alpha_{ij}^k, \beta_{ij}^k, \gamma_{ij}^k, \theta_{ij}^k\right),\ \tilde{w}_j^k=\left(w_{j1}^k, w_{j2}^k, w_{j3}^k, w_{j4}^k\right)$$

$$\tilde{D}^k = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{bmatrix} \tilde{x}_{11}^k & \tilde{x}_{12}^k & \cdots & \tilde{x}_{1j}^k & \cdots & \tilde{x}_{1n}^k \\ \tilde{x}_{21}^k & \tilde{x}_{22}^k & \cdots & \tilde{x}_{2j}^k & \cdots & \tilde{x}_{2n}^k \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ \tilde{x}_{i1}^k & \tilde{x}_{i2}^k & \cdots & \tilde{x}_{ij}^k & \cdots & \tilde{x}_{in}^k \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ \tilde{x}_{m1}^k & \tilde{x}_{m2}^k & \cdots & \tilde{x}_{mj}^k & \cdots & \tilde{x}_{mn}^k \end{bmatrix} \tag{4.1}$$

***Step 3:*** Aggregation of decision-makers' pulled opinion to compute aggregated rating of alternatives $\left(\tilde{x}_{ij}\right)$ and aggregated weight of criteria $\left(\tilde{w}_j\right)$.

$$\tilde{x}_{ij} = (\alpha_{ij}, \beta_{ij}, \gamma_{ij}, \theta_{ij});$$

$$\alpha_{ij} = \min_k \{\alpha_{ij}^k\} \tag{4.2}$$

$$\beta_{ij} = \frac{1}{K}\sum_{k=1}^{K} \beta_{ij}^k \tag{4.3}$$

$$\gamma_{ij} = \frac{1}{K}\sum_{k=1}^{K} \gamma_{ij}^k \tag{4.4}$$

$$\theta_{ij} = \max_k \{\theta_{ij}^k\} \tag{4.5}$$

Also $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3}, w_{j4})$

$$w_{j1} = \min_k \{w_{j1}^k\} \tag{4.6}$$

$$w_{j2} = \frac{1}{K}\sum_{k=1}^{K} w_{j2}^k \tag{4.7}$$

$$w_{j3} = \frac{1}{K}\sum_{k=1}^{K} w_{j3}^k \tag{4.8}$$

$$w_{j4} = \min_k \{w_{j4}^k\} \tag{4.9}$$

***Step 4:*** Establish initial decision making matrix.

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{4.10}$$

***Step 5:*** Normalize the decision making data to obtain the normalized decision matrix.

$$\tilde{r}_{ij} = \left(\frac{\alpha_{ij}}{\theta_j^*}, \frac{\beta_{ij}}{\theta_j^*}, \frac{\gamma_{ij}}{\theta_j^*}, \frac{\theta_{ij}}{\theta_j^*}\right); j \in B;\ \theta_j^* = \max_i \{\theta_{ij}\}; \tag{4.11}$$

$$\tilde{r}_{ij} = \left(\frac{\alpha_j^-}{\theta_{ij}}, \frac{\alpha_j^-}{\gamma_{ij}}, \frac{\alpha_j^-}{\beta_{ij}}, \frac{\alpha_j^-}{\alpha_{ij}}\right); j \in C; \alpha_j^- = \min_i \{\alpha_{ij}\} \tag{4.12}$$

$B$: Set of benefit criteria (whose higher values are highly preferred)

$C$: Set of cost/adverse criteria (whose lower values are generally preferred)

***Step 6:*** Construct weighted normalized decision matrix.

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j \tag{4.13}$$

***Step 7:*** Calculate the partial matrices of dominance $\phi_c\left(\tilde{A}_p, \tilde{A}_q\right)$ using Eq. (4.14). The term $\phi_c\left(\tilde{A}_p, \tilde{A}_q\right)$ represents the contribution of the criterion $c$ to the function $\delta\left(\tilde{A}_p, \tilde{A}_q\right)$ i.e. global dominance when comparing alternative $p$ with alternative $q$.

$$\phi_c\left(\tilde{A}_p, \tilde{A}_q\right) = \begin{cases} d\left(\tilde{v}_{pc}, \tilde{v}_{qc}\right), & If\ \left[m\left(\tilde{v}_{pc}\right) - m\left(\tilde{v}_{qc}\right)\right] > 0 \\ 0, & If\ \left[m\left(\tilde{v}_{pc}\right) - m\left(\tilde{v}_{qc}\right)\right] = 0 \\ -d\left(\tilde{v}_{pc}, \tilde{v}_{qc}\right), & If\ \left[m\left(\tilde{v}_{pc}\right) - m\left(\tilde{v}_{qc}\right)\right] < 0 \end{cases} \tag{4.14}$$

In this expression (Eq. 4.14), $m\left(\tilde{v}_{pc}\right)$ and $m\left(\tilde{v}_{qc}\right)$ stands for the defuzzified values of the fuzzy number $\tilde{v}_{pc}$ and $\tilde{v}_{qc}$, respectively (obtained from Chen et al., 1997). Here, $\tilde{v}_{pc}$ and $\tilde{v}_{qc}$ represent weighted normalized rating of alternative $p$ and $q$ respectively, for a particular criterion $c$ as obtained in Step 6. The term $d\left(\tilde{v}_{pc}, \tilde{v}_{qc}\right)$ designates the distance between the two fuzzy numbers $\tilde{v}_{pc}$ and $\tilde{v}_{qc}$ that can be computed using the formula given in (Chen, 2000). Three cases can occur in (Eq. 4.14):

i. if the value $\left[m\left(\tilde{v}_{pc}\right) - m\left(\tilde{v}_{qc}\right)\right]$ is positive, it represents a dominance (alternative $p$ is dominating alternative $q$);
ii. if the value $\left[m\left(\tilde{v}_{pc}\right) - m\left(\tilde{v}_{qc}\right)\right]$ is zero, there is null dominance and
iii. if the value $\left[m\left(\tilde{v}_{pc}\right) - m\left(\tilde{v}_{qc}\right)\right]$ is negative, it represents negative dominance (alternative $q$ is dominating alternative $p$).

A separate formulation can be well attributed if fuzzy subtraction formula $(-)$ is employed instead of fuzzy distance measure between $\tilde{v}_{pc}$ and $\tilde{v}_{qc}$. The dominance of alternative $p$ over $q$ (for a particular criterion $c$) can also be computed as in (Eq. 4.15) as follows.

$$\phi_c\left(\tilde{A}_p, \tilde{A}_q\right) = \tilde{v}_{pc}(-)\tilde{v}_{qc} \tag{4.15}$$

Here $(-)$ represents fuzzy subtraction operator (Chen and Chen, 2007). $\tilde{v}_{pc}$ and $\tilde{v}_{qc}$ represent weighted normalized rating of alternatives $p$ and $q$ respectively for a particular criterion $c$. In this case, partial dominance measure i.e. $\phi_c(\tilde{A}_p, \tilde{A}_q)$ also becomes a fuzzy number. Whilst, in (Eq. 4.14), the distance measure between two fuzzy numbers i.e. $d(\tilde{v}_{pc}, \tilde{v}_{qc})$ being a positive value; appropriate sign has to be considered separately to indicate whether alternative $p$ is dominating alternative $q$ (positive dominance); or alternative $p$ is dominated by alternative $q$ (negative dominance).

***Step 8:*** The final matrix of dominance is obtained by summing up the partial matrices of dominance of each criterion.

$$\delta(\tilde{A}_p, \tilde{A}_q) = \sum_{c=1}^{n} \phi_c(\tilde{A}_p, \tilde{A}_q) \quad \forall(p,q) \tag{4.16}$$

If, (Eq. 4.15) is applied to compute partial matrices of dominance; the global dominance measure i.e. $\delta(\tilde{A}_p, \tilde{A}_q)$ becomes a fuzzy number; and hence, it is to be defuzzified again to proceed for computing $\xi$ (refer to Step 9).

***Step 9:*** Calculate the global value of the alternative $\xi$ by normalizing the final matrix of dominance according to the following expression.

$$\xi = \frac{\sum \delta(p,q) - \min \sum \delta(p,q)}{\max \sum \delta(p,q) - \min \sum \delta(p,q)} \tag{4.17}$$

***Step 10:*** Ordering the values $\xi$ provides the rank of each alternative. The best alternative is one that has the highest value of $\xi$.

## 4.4 Case Empirical Illustration

A case empirical analysis has been demonstrated to verify application potential of the proposed decision support module. The study articulates a supplier selection problem in consideration with green and resiliency criteria. It has been assumed that all of the candidate suppliers have achieved the requirements of traditional selection criteria (product price, delivery time, quality and service) of equal extent and hence, the best supplier has to be chosen in view of green as well as resiliency criteria. Pertinent attributes (criteria) relevant to g-resilient supplier selection have been listed in Table 4.1a. The following criteria: Use of environment friendly technology ($C_1$), Use of environment friendly materials ($C_2$), Green market share ($C_3$), Partnership with green organizations ($C_4$), Management commitment ($C_5$), Adherence to environmental policies ($C_6$), Green R & D projects ($C_7$), Staff Training ($C_8$), Lean process planning ($C_9$), Design for environment ($C_{10}$), Environmental certification ($C_{11}$), and Pollution control initiatives ($C_{12}$) etc. have been considered as green criteria. Similarly, the following criteria: Investment in capacity buffers ($C_{13}$), Responsiveness ($C_{14}$), Capacity for holding strategic inventory stocks for crises ($C_{15}$) etc. have been considered as resiliency criteria. The definitions of criteria (from both green and resilient dimensions or perspectives) in relation to g-resilient supplier selection have been described in Table 4.1b.

Assuming a group of four Decision-Makers (DMs) [DM1, DM2, DM3, DM4] have been employed to evaluate four candidate suppliers ($S_1$, $S_2$, $S_3$, $S_4$) in view of aforementioned green as well as resiliency criteria ($C_1$ to $C_{15}$); a 7-point fuzzy linguistic scale has been chosen to collect subjective judgment of the individual member of the decision-making group in regards of criteria weight as well as rating of alternative suppliers with respect to evaluation criteria. The following linguistic terms set: {Very Low (VL), Low (L), Medium Low (ML), Medium/ Moderate (M), Medium High (MH), High (H) and Very High (VH)} have been explored towards assigning criteria weight. The linguistic terms set: {Very Poor (VP), Poor (P), Medium Poor (MP), Fair (F), Medium Good (MG), Good (G) and Very Good (VG)} have been used to assess rating of alternative suppliers with respect to various criteria. The aforesaid two linguistic terms sets along with their fuzzy representations have been depicted in Table 4.2.

The decision making group has been instructed to utilize those linguistic scales for assigning criteria weight and rating of alternatives in terms of linguistic variables. Since all the evaluation criteria being subjective in nature; such kind of linguistic assessment is well justified. However, linguistic human judgment always bears some degree of uncertainty in terms of incompleteness as well as inconsistency; therefore, ambiguity and vagueness of imprecise data can efficiently be dealt with fuzzy set theory. Hence, linguistic decision making information as provided by the expert group has been converted into appropriate fuzzy numbers; then, by exploring fuzzy decision making approaches, the final decision outcome is achieved. Table 4.3 represents criteria weight expressed in linguistic terms as given by the Decision-Makers (DMs). The subjective ratings of alternative suppliers ($S_1$, $S_2$, $S_3$, $S_4$) with respect to criteria as assessed by the DMs have been depicted in Tables (4.4a-4.4d), respectively. Linguistic data have been transformed into appropriate fuzzy numbers in accordance with Table 4.2.

By using fuzzy aggregation rule, aggregated fuzzy ratings of alternatives with respect to criteria have been computed and tabulated in Table 4.5. Thus, initial decision support matrix has been arrived (as shown in Table 4.5). Similarly, aggregated fuzzy weights of criteria have been computed as shown in Table 4.6. The fuzzy decision making matrix (as shown in Table 4.5) along with fuzzy criteria weights (furnished in Table 4.6) have been utilized in the proposed DSS. The ranking order of alternative suppliers, obtained thereof, have been compared to that of Fuzzy-TOPSIS, Fuzzy-VIKOR and finally Fuzzy-TODIM.

## 4.5 Results on Exploration of the Proposed DSS: Comparison with Fuzzy-TOPSIS and Fuzzy-VIKOR

In the proposed dominance-based decision making approach, by utilizing the data from the weighted normalized decision matrix (as obtained by Eq. 4.13) as shown in Table 4.8, the partial matrices of dominance $\phi_c\left(\tilde{A}_p, \tilde{A}_q\right)$ between alternative pairs (with respect to individual criterion) has been computed using (Eq. 4.14) and shown in Table 4.9. In constructing Table 9 (the partial matrices of dominance), the fuzzy distance measure formula has been utilized (Chen, 2000). The Euclidian distance between two fuzzy numbers being a crisp value (positive), proper sign consideration should be taken care of to indicate whether an alternative is dominating the other one or it is dominated by the other one. By utilizing the data from the partial matrices of dominance, the final matrices of dominance has been computed by using (Eq. 4.16) and shown in Table 4.10. Finally, the global value of alternative suppliers $\xi_i | i = 1,2,...,n$ have been computed by normalizing the final matrix of dominance according to (Eq. 4.17) and shown in Table 4.11. The ranking order of alternative suppliers appears as: $S_4$>$S_3$>$S_2$>$S_1$ (shown in Table 4.11).

A separate computational scheme can be well articulated if fuzzy subtraction operator is utilized instead of fuzzy distance measure in order to compute the partial matrices of dominance. By using (Eq. 4.15) i.e. the fuzzy subtraction operator, the partial matrices of dominance $\phi_c\left(\tilde{A}_p, \tilde{A}_q\right)$ between alternative pairs (with respect to individual criteria) has been computed and shown in Table 4.12. Since, subtraction of two fuzzy numbers yields another fuzzy number; hence, the dominance between alternative pairs with respect to criteria has been expressed in terms of fuzzy numbers as shown in Table 4.12. Now, final matrices of dominance have been constructed by using (Eq. 4.16) and shown in Table 4.13.

Finally, the global dominance measure (for alternative suppliers), corresponding crisp score, normalized crisp score have been determined; based on which candidate suppliers have been ranked accordingly (Table 4.14). The ranking order of alternative suppliers appears as: $S_4>S_3>S_2>S_1$ (Table 4.14), same as in case of Fuzzy-TOPSIS (as obtained from Table 4.15) and Fuzzy-VIKOR (as shown in Table 4.16).

## 4.6 Suppliers' Ranking Based on G-Resilient Index: Identification of Ill-Performing areas

Aforesaid sections deal with g-resilient supplier selection in view of a consolidated list of criteria arising from two separate dimensions i.e. green and resilience. Alternative suppliers have been ranked by the proposed dominance based approach. The ranking order obtained thereof has been compared to that of obtained through Fuzzy-TOPSIS and Fuzzy-VIKOR. However, these approaches seem incapable to estimate an overall performance index (g-resilient index i.e. GRI) of individual suppliers. Computation of a unique g-resilient index is felt necessary to ascertain overall g-resilience performance index of supplier alternatives. Alternative suppliers can also be ranked based on their g-resilient index.

In order to compute, a unique g-resilient index of candidate suppliers, a different nomenclature of criteria-hierarchy has been conceptualized (as shown in Table 4.17) to frame mathematical formulations of the procedural steps. Here, all pertinent attributes ($C_1$ to $C_{15}$ of Table 4.1a) have been divided into two broad dimensions (or main criteria/ performance indicators) $PD_j \big| j=1,2.$ i.e. green performance ($PD_1$) and resilience performance ($PD_2$). Each main-criteria has further been divided into some sub-criteria $C_{jl}$. Under green performance ($PD_1$), a total of twelve sub-criteria have been assumed $(j=1;\ l=1,2,...,12)$. These have been denoted as: Use of environment friendly technology ($C_{11}$), Use of environment friendly materials ($C_{12}$), Green market share ($C_{13}$), Partnership with green organizations ($C_{14}$), Management commitment ($C_{15}$), Adherence to environmental policies ($C_{16}$), Green R & D projects ($C_{17}$), Staff Training ($C_{18}$), Lean process planning ($C_{19}$), Design for environment ($C_{1,10}$), Environmental certification ($C_{1,11}$), Pollution control initiatives ($C_{1,12}$) etc. Under resilience performance ($PD_2$), three sub-criteria have been assumed $(j=2;\ l=1,2,3)$. These have been denoted as: Investment in capacity buffers ($C_{21}$), Responsiveness ($C_{22}$), Capacity for holding strategic inventory stocks for crises ($C_{23}$) etc. Such a nomenclature has been adopted in this part of work to understand various computational formulae easily (Refer to Eqs. 4.18-4.20).

$$\tilde{x}_{ij} = \frac{\sum_{l=1}^{L} \tilde{w}_{jl} \otimes \tilde{x}_{ijl}}{\sum_{l=1}^{L} \tilde{w}_{jl}} \tag{4.18}$$

Here, $\tilde{x}_{ijl}$ is the aggregated fuzzy rating of $i^{th}$ alternative with respect to $l^{th}$ sub-criterion $C_{jl}$ which is under $j^{th}$ main-criterion $PD_j$. Also $\tilde{w}_{jl}$ is the aggregated fuzzy weight of $l^{th}$ sub-criterion $C_{jl}$ which is under $j^{th}$ main-criterion $PD_j$. $\tilde{x}_{ij}$ is the computed fuzzy rating of $i^{th}$ alternative with respect to $j^{th}$ main criterion $PD_j$. It is also assumed that $j^{th}$ main criterion $PD_j$ consists of a total $L$ number of sub-criteria.

Now, g-resilient index of alternative supplier can be computed as follows:

$$GRI_i = \frac{\sum_{j=1}^{n} \tilde{w}_j \otimes \tilde{x}_{ij}}{\sum_{j=1}^{n} \tilde{w}_j} \tag{4.19}$$

In this expression, $\tilde{x}_{ij}$ is the computed fuzzy rating of $i^{th}$ alternative with respect to $j^{th}$ main criterion $PD_j$; $\tilde{w}_j$ being the aggregated fuzzy weight of $j^{th}$ main-criterion $PD_j$. Also, $GRI_i$ be the g-resilient index of $i^{th}$ alternative. The total number of main criteria is assumed as $n$ Candidate suppliers can be ranked based on their g-resilient index. The suppliers' g-resilient indices being fuzzy numbers have to be defuzzified to get the final ranking order.

Evaluation of g-resilient index not only helps in selecting appropriate suppliers adhering to green and resilient practices, but also helps individual suppliers to identify ill-performing areas involved in implementing an appropriate action requirement plan to improve the g-resilient performance. The decision making information in regards of weights of sub-criteria and ratings of alternatives with respect to criteria have been the same as depicted in Table 4.3 and Tables 4.1a-4.1d, respectively; however, a diffident notation have been used herein as compared to the previous sections. The aggregated fuzzy ratings of alternatives (refer to the initial decision matrix in Table 4.5) and the fuzzy priority weight of sub-criteria (refer to Table 4.6) have been explored here to compute GRI of candidate suppliers. Since, supplier selection decision has to be made based on two distinct performance criteria (green and resiliency); while aggregating performance extents of greenness and resiliency, priority weights need to be assigned to each of the performance dimensions (PD1 and PD2). Different Decision-Makers have their own opinion, and hence, the expert group has been requested to assign priority weights for PD1 and PD2 in a subjective manner (linguistic judgment) as depicted in Table 4.18. Linguistic judgment has been transformed into appropriate fuzzy numbers as per Table 4.2. Next, aggregated fuzzy weight of main performance dimensions viz. PD1 and PD2 have been computed and shown in Table 4.18. Now, by exploring aggregated fuzzy ratings of alternatives with respect to sub-criteria (refer to Table 4.5) and aggregated fuzzy weights of sub-criteria (refer to Table 4.6), ratings of alternative suppliers with respect to main performance dimensions PD1 and PD2 have been computed using (Eq. 4.18) and furnished in Table 4.19.

Finally, computed fuzzy ratings of PD1 and PD2 (for individual supplier alternatives) and aggregated fuzzy weights of PD1 and PD2 have been combined using Eq. (4.19) to compute the g-resilient index $(GRI_i)|i = 1,2,3,4$ of individual suppliers. Suppliers' g-resilient indices being fuzzy numbers; have been defuzzified further to obtain the final ranking order (refer to Table 4.20). The ranking order appears as: $S_4 > S_3 > S_2 > S_1$.

In order to identify suppliers' ill-performing areas to improve g-resilient performance extent, a Fuzzy Performance-Importance Index (FPII) has been computed herein; FPII combines the rating and weight of each sub-criterion. FPII represents an effect which influences suppliers' g-resilient performance level. The degree of contribution of g-resilient performance for a sub-criterion decreases with decreasing FPII. Thus, the score of the FPII of a sub-criterion is used for identifying the ill-performing areas for achievement of satisfactory g-resilient performance level. The concept of FPII has been well articulated in (Lin et al., 2006; Samantra et al., 2013).

If $\left\lfloor \tilde{w}_{jl} \otimes \tilde{x}_{ijl} \right\rfloor$ is used directly to calculate the $FPII_{ijl}$ (for $i^{th}$ supplier) in relation to sub-$l^{th}$ criterion $C_{jl}$ (which is under $j^{th}$ main-criterion $PD_j$), the importance weights $\tilde{w}_{jl}$ will neutralize the performance ratings in calculating $FPII_{ijl}$; in this case, it will become impossible to identify the actual ill-performing areas (low performance rating and high importance). If $\tilde{w}_{jl}$ is high, then the transformation $\left\lfloor (1,1,1,1)(-)\tilde{w}_{jl} \right\rfloor$ is low. Consequently, to elicit a sub-criterion with low performance rating and high importance, the fuzzy performance-importance index $FPII_{ijl}$ indicating the effect of each sub-criterion that contributes to suppliers' g-resilient performance, is defined as (Eq. 4.20)

$$FPII_{ijl} = \left\lfloor (1,1,1,1)(-)\tilde{w}_{jl} \right\rfloor \otimes \tilde{x}_{ijl} \tag{4.20}$$

Since fuzzy numbers do not always yield a totally ordered set in the manner of real numbers, the $FPII_{ijl}$ s must be ranked. Suppliers can easily identify ill-performing sub-criteria by ranking FPIIs of individual sub-criteria.

The FPII for alternative suppliers with respect to individual sub-criteria have been computed (using Eq. 4.20) and tabulated in Table 4.21. The performance extents of candidate suppliers with respect to various sub-criterions have thus been ranked as shown in Table 4.21. Performance ranking of supplier alternatives with respect to green as well as resiliency criteria helps in identifying ill (poor) performing areas which require future improvement to boost up overall g-resilience performance extent.

It can be described from Table 4.21 that supplier $S_1$ is strong enough for criteria $C_{16}$ (Adherence to environmental policies) but need a huge improvement for criteria $C_{12}$ (Use of environment friendly materials). Supplier $S_2$ is fair enough for resiliency performance criteria $C_{22}$ (Responsiveness) and need valuable enhancement for criteria

$C_{1,\ 11}$ (Environmental certification). Similarly, supplier $S_3$ is having good control over the criteria $C_{13}$ (Green market share) while criteria $C_{1,\ 11}$ (Environmental certification) needs to be add more value. For the supplier $S_4$ resiliency performance criteria $C_{22}$ (Responsiveness) is the most appreciable one while criteria $C_{1,\ 11}$ (Environmental certification) is needed for necessary further improvements again.

## 4.7 Comparison with Fuzzy-TODIM

As the decision support system proposed herein bears some similarities with respect to TODIM, it is felt necessary to compare ranking orders of alternative g-resilient suppliers (that has been arrived in the aforementioned research) to that of TODIM. As all of the evaluation criteria (towards g-resilient suppliers selection), selected in this work, have been evaluated in a subjective manner rather than objective assessment, application of Fuzzy-TODIM seems appropriate in the current problem domain. The mathematical background along with computational formulae of Fuzzy-TODIM in the context of MCDM could be well retrieved from (Krohling and de Souza, 2012).

The steps on applying fuzzy-TODIM have been narrated below.

1. Computation of crisp weight of criteria by defuzzifying aggregated fuzzy criteria weight.
2. Determination of reference weight and relative weight of criteria.
3. Computation of dominance between alternative pairs by means of prospect function and by exploring the formulation of fuzzy distance measure as proposed by (Krohling and de Souza, 2012).
4. Computation of global matrices of dominance.
5. Computation of the global index value of alternatives and thus deriving final ranking order.

In this computation, aggregated fuzzy criteria weight as depicted in Table 4.6 have been converted into corresponding crisp weights (by using the formula as reported in Chen et al., 1997) and shown in Table 4.22. It has been found that the criteria $C_{11}$ and $C_{15}$ correspond to maximum weight (0.925) and hence, this value has been treated as reference weight. The relative weights of remaining criteria have been computed next with respect to the reference weight and tabulated in Table 4.22. By utilizing the gain/loss function of TODIM as retrieved from prospect theory, the partial matrices of dominance has been obtained (as shown in Table 4.23). In this computation, $\theta$(the attenuation factor) has been assumed equal to 1. After constructing partial matrices of dominance, the final matrices of dominance has been arrived (refer to Table 4.24); based on which the global measure value of each alternative has been determined (Table 4.25). The ranking order of candidate g-resilient suppliers appears as: $S_4 > S_3 > S_2 > S_1$; same as obtained in all cases attempted just before.

## 4.8 Discussion

Efficient decision support system has always been a requirement for the supply chain managers to solve a variety of industrial decision making problems in different decision environments. Application potential of the proposed decision support framework based on dominance theory for solving multi-criteria decision making problems has possibly got a positive signal in the foregoing study. Managers from various industries are hereby advised to adopt the guidelines for solving complex decision making problems. The superiority of the proposed approach has been summarized below.

1. The obtained results are accurate and present a uniform ranking order even in comparison with other well-known MCDM approaches like Fuzzy-TOPSIS and Fuzzy-VIKOR.
2. This method is flexible enough and can be solved using either fuzzy distance operator or fuzzy subtraction operator without noticeable navigation on the results.
3. This study would likely help supply chain manager to find out suppliers' ill (poor)-performing areas so that the necessary action can be taken to improve that particular area.

## 4.9 Concluding Remarks

In the foregoing work, a g-resilient supplier selection framework has been anticipated in view of a decision making scenario aiming to select the best possible g-resilient supplier by considering green as well as resiliency criteria. Subjectivity of suppliers evaluation criteria have been undertaken by means of fuzzy set theory.

The work exhibits application potential of a novel decision support framework based on dominance theory in the context of g-resilient supplier selection. The ranking order of candidate g-resilient suppliers has been compared to that of Fuzzy-TOPSIS, Fuzzy-VIKOR as well as Fuzzy-TODIM. Apart from this, a unified attempt has also been incorporated to determine a unique g-resilient performance index with respect to individual suppliers, and thereby, identifying ill-performing areas to be improved in future towards achieving desired level of g-resilient performance. It has been noticed that for the current supplier selection problem, the best and the worst g-resilient suppliers appear the same in all aforementioned approaches.

Table 4.1a: Pertinent attributes relevant to g-resilient supplier selection

| Dimensions | Criteria | Citations |
|---|---|---|
| Green criteria | Use of environment friendly technology, $C_1$ | Awasthi et al., 2010; Handfield et al., 2002; Lee et al., 2009; Nielsen et al., 2014 |
| | Use of environment friendly materials, $C_2$ | Awasthi et al. 2010; Humphreys et al. 2003; Handfield et al., 2002; Handfield et al., 2005; Nielsen et al., 2014 |
| | Green market share, $C_3$ | Awasthi et al., 2010; Handfield et al., 2005; Nielsen et al., 2014 |
| | Partnership with green organizations, $C_4$ | Awasthi et al., 2010; Humphreys et al., 2003; Handfield et al., 2005; Nielsen et al., 2014 |
| | Management commitment, $C_5$ | Awasthi et al., 2010; Handfield et al., 2005; Nielsen et al., 2014 |
| | Adherence to environmental policies, $C_6$ | Awasthi et al., 2010; Humphreys et al., 2003; Handfield et al., 2005; Nielsen et al., 2014 |
| | Green R & D projects, $C_7$ | Awasthi et al., 2010; Lee et al., 2009, Tseng and Chiu, 2013; Awasthi et al., 2010; Orji and Wei, 2014; Amindoust et al., 2012; Nielsen et al., 2014 |
| | Staff Training, $C_8$ | Barbarosoglu and Yazgac, 1997; Humphreys et al., 2003; Awasthi et al., 2010; Handfield et al., 2005 |
| | Green process planning, $C_9$ | Ghadimi and Heavey, 2014; Nielsen et al., 2014; Hashemi et al., 2015; Awasthi et al., 2010; Nielsen et al., 2014 |
| | Design for environment, $C_{10}$ | Akili, 2009; Awasthi et al., 2010; Humphreys et al., 2003; Handfield et al., 2002; Nielsen et al., 2014 |
| | Environmental certification, $C_{11}$ | Humphreys et al., 2003; Nielsen et al., 2014; Hashemi et al., 2015; Lee et al., 2009; Awasthi et al., 2010; Nielsen et al., 2014 |
| | Pollution control initiatives, $C_{12}$ | Tseng and Chiu, 2013; Yeh and Chuang, 2011; Awasthi et al., 2010; Zhu et al., 2010; Orji and Wei, 2014; Bai and Sarkis, 2010b; Amindoust et al., 2012; Azadnia et al., 2012; Humphreys et al., 2003; Lee et al. 2009; Nielsen et al., 2014 |
| Resiliency criteria | Investment in capacity buffers, $C_{13}$ | Chou and Chang, 2008; Hervani et al., 2005; Epstein and Wisner, 2001;Yazlali and Erhun, 2009; Li and Debo, 2009 |
| | Responsiveness, $C_{14}$ | Özgen et al., 2008; Handfield et al., 2005; Yazlali and Erhun, 2009; Tang and Musa, 2011; Haldar et al., 2012 |
| | Capacity for holding strategic inventory stocks for crises, $C_{15}$ | Chopra and Sodhi, 2004; Jüttner et al., 2003; Yazlali and Erhun, 2009; Tang, 2006; Haldar et al., 2012 |

Table 4.1b: Definitions of criteria in relation to g-resilient supplier selection

| Criteria | Definitions |
|---|---|
| Use of environment friendly technology | In order to protect the environment from industrial wastes (or residuals), a clean and environment-friendly technology must be explored. This emphasizes the use of environment-friendly technology that conserves energy and fossil fuel resources (Awasthi et al., 2010). This must ensure enhancement of manufacturing capabilities, design capabilities, and ability to cope up with latest technology (Chou and Chang, 2008). It facilitates new product/process development of the supplier's side that can provide new and upgraded products to the firm (Lee et al., 2009; Shaik and Kader, 2011). |
| Use of environment friendly materials | Organizations must encourage their suppliers to provide environment friendly materials to avoid any after effects. Green purchasing can address issues such as reduction of waste produced, material substitution through environmental sourcing of raw materials, and waste minimization of hazardous material (Rao and Holt, 2005). Therefore, companies are increasingly managing their suppliers' environmental performance to ensure that the products supplied by them are environmentally-friendly; and these are produced using environmentally-friendly processes. |
| Green market share | It can be evaluated in view of the effort of suppliers in producing green products. It includes green image of the supplier and better stakeholder relationship. It also includes the extent of retention of customers with green purchasing habits (Awasthi et al., 2010). |
| Partnership with green organizations | This criterion reflects a strong affection towards organizations working under green manufacturing practice. It includes association, collaboration and partnership with green suppliers, environmental organizations (Awasthi et al., 2010). |
| Management commitment | This refers to the involvement of management towards implementation of green programs in order to improve the environmental performance (Awasthi et al., 2010). Environmental management improves quality of products with regard to environmental and value management such as environmental policies, their implementation and respective certifications (Shaik and Kader, 2011). |
| Adherence to environmental policies | It is basically the conformance to environmental regulatory standards (Awasthi et al., 2010). This criterion also includes the necessity of reviewing the supplier's environmental policy to obtain a condition of zero environmental harm. |
| Green R & D projects | It is the movement of R&D projects and production habits from being conventional to green. It is also defined as the supplier's green R&D capability to meet current and future demand of the firm (Shaik and Kader, 2011). Green R&D projects should focus on green product and green process planning (Awasthi et al., 2010). |

Table 4.1b (continued): Definitions of criteria in relation to g-resilient supplier selection

| | |
|---|---|
| Staff Training | It is the availability of adequate information to the workers in regards of green production system and applicability of green policies into the manufacturing practices. Suppliers should emphasize on staff training to fulfill environmental targets (Awasthi et al., 2010). |
| Lean process planning | The main focus of lean process planning is to improve green attributes (namely resource consumption and environmental impacts) of production processes by optimizing process elements, process courses, and process projects (Cao et al., 2002; He et al., 2007). Green process planning for manufacturing system emphasizes on reducing energy and resource consumption, avoid wastage, reduce noise and harmful environmental effects during manufacturing without sacrificing productivity, quality, and efficiency (Gogoi and Hazarika, 2014). |
| Design for environment | It is the emphasis on environment-friendly design for manufacturing practices so that the product can be recycled, reused, re-manufactured along with disassembly as well as disposal. It necessitates checking of supplier's design for environment capability (e.g. design for disassembly) so that the product becomes more environmental-friendly (Humphreys et al., 2003). |
| Environmental certification | Suppliers should achieve environment-related certifications, such as ISO 14000 (Shaik and Kader, 2011). For suppliers claiming to be green, the most tangible activity is to get environmental certificate or labels like ISO14000, eco-friendly label and carbon footprint label, etc. (Banaeian et al., 2015). |
| Pollution control initiatives | This shows the effort or extent of pollution minimization initiatives related to air emissions, waste water disposal, solid wastes, energy consumption, use of harmful materials and hazardous wastes etc. (Awasthi et al., 2010). It is the extent of technology available to control all kind of pollutions like average volume of air pollutants, waste water, solid waste, and harmful materials released (Hashemi et al., 2015). |

Table 4.1b (continued): Definitions of criteria in relation to g-resilient supplier selection

| | |
|---|---|
| Investment in capacity buffers | Buffer (also called safety stock) capacity is defined as the level of additional stock preserved to mitigate the risk of stock-outs due to uncertainties in supply and demand (Haldar et al., 2012). A buffer stock scheme (commonly implemented as intervention storage, the 'ever-normal granary') is an attempt to use commodity storage for the purposes of stabilising prices in an entire economy or, more commonly, an individual (commodity) market. Specifically, commodities are bought when there is a surplus in the economy, stored, and are then sold from these stores when there are economic shortages in the economy. The volume of buffer capacity should be the optimal. |
| Responsiveness | Responsiveness is the ability of suppliers to respond with the fluctuating market demands in minimal possible time. It is also known as the response speed of suppliers towards unpredictable market demand, which necessitates supply of more variety (mass-customized product) at shorter notice. It helps suppliers' firms for gaining competitive advantage in the market (Haldar et al., 2012). |
| Capacity for holding strategic inventory stocks for crises | It shows zero availability loss replenishment and stock turn (Handfield et al., 2005). The strategic inventory stock must be at its defined level as protective capacity is essential to cope up with any uncertain demand. Inventory stock should be at optimum level as it will create a huge loss if maintained above/below the level prescribed so far. Strategic inventory stock is essential for the assurance of prompt delivery performance even in crisis (like strike, natural disaster, transport delay etc.). The resilience performance of the firm can be enhanced by ensuring delivery in case of emergency. An optimal (economic) volume of inventory should be maintained to survive in adverse situations. |

Table 4.2: Seven point fuzzy linguistic scale for quantifying likelihood of occurrence (Source: Chen et al., 2006)

| Linguistic terms for criteria ratings | Linguistic terms for assigning criteria weights | Generalized trapezoidal Fuzzy Numbers |
|---|---|---|
| Very Poor, VP | Very Low, VL | (0,0,0.1,0.2) |
| Poor, P | Low, L | (0.1,0.2,0.2,0.3) |
| Medium Poor, MP | Medium Low, ML | (0.2,0.3,0.4,0.5) |
| Fair, F | Medium/ Moderate, M | (0.4,0.5,0.5,0.6) |
| Medium Good, MG | Medium High, MH | (0.5,0.6,0.7,0.8) |
| Good, G | High, H | (0.7,0.8,0.8,0.9) |
| Very Good, VG | Very High, VH | (0.8,0.9,1,1) |

Table 4.3: Priority weight of criteria

| Criteria | Linguistic priority weight given by the decision-makers | | | |
|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 |
| $C_1$ | H | H | H | H |
| $C_2$ | VH | VH | H | H |
| $C_3$ | MH | MH | H | H |
| $C_4$ | H | H | H | H |
| $C_5$ | VH | VH | VH | H |
| $C_6$ | MH | H | H | H |
| $C_7$ | H | H | H | H |
| $C_8$ | MH | H | VH | VH |
| $C_9$ | H | H | VH | VH |
| $C_{10}$ | H | H | H | H |
| $C_{11}$ | VH | VH | VH | VH |
| $C_{12}$ | H | VH | H | VH |
| $C_{13}$ | H | H | H | H |
| $C_{14}$ | H | MH | MH | MH |
| $C_{15}$ | VH | VH | VH | VH |

Table 4.4a: Appropriateness rating of supplier alternative **$S_1$** with respect to the evaluation of criteria

| Criteria | Ratings expressed in linguistic terms given by the DMs | | | |
|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 |
| $C_1$ | P | P | P | P |
| $C_2$ | MP | P | F | F |
| $C_3$ | P | P | MP | MP |
| $C_4$ | F | MG | MG | MG |
| $C_5$ | MP | F | MG | MG |
| $C_6$ | F | F | F | F |
| $C_7$ | MG | F | G | G |
| $C_8$ | MP | F | F | F |
| $C_9$ | F | F | F | F |
| $C_{10}$ | MP | F | F | MP |
| $C_{11}$ | MG | F | MG | F |
| $C_{12}$ | F | F | F | F |
| $C_{13}$ | MP | F | F | F |
| $C_{14}$ | F | MP | F | MP |
| $C_{15}$ | F | F | F | F |

Table 4.4b: Appropriateness rating of supplier alternative **$S_2$** with respect to the evaluation of criteria

| Criteria | Ratings expressed in linguistic terms given by the DMs | | | |
|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 |
| $C_1$ | F | F | F | MG |
| $C_2$ | F | MG | MG | F |
| $C_3$ | MP | F | F | F |
| $C_4$ | F | F | F | F |
| $C_5$ | MG | F | MG | F |
| $C_6$ | F | F | F | F |
| $C_7$ | MP | F | F | F |
| $C_8$ | MG | G | F | F |
| $C_9$ | F | F | F | MP |
| $C_{10}$ | MP | MP | MP | MP |
| $C_{11}$ | F | MP | F | MP |
| $C_{12}$ | F | F | F | F |
| $C_{13}$ | MG | F | F | MG |
| $C_{14}$ | G | MG | MG | MG |
| $C_{15}$ | MG | MG | F | F |

Table 4.4c: Appropriateness rating of supplier alternative $\mathbf{S_3}$ with respect to the evaluation of criteria

| Criteria | Ratings expressed in linguistic terms given by the DMs | | | |
|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 |
| $C_1$ | F | F | MG | G |
| $C_2$ | G | G | G | G |
| $C_3$ | MG | MG | G | G |
| $C_4$ | G | G | G | G |
| $C_5$ | F | MG | MG | MG |
| $C_6$ | F | F | F | F |
| $C_7$ | G | G | G | MG |
| $C_8$ | VG | G | VG | G |
| $C_9$ | G | G | G | G |
| $C_{10}$ | MG | G | G | G |
| $C_{11}$ | G | G | MG | MG |
| $C_{12}$ | F | F | MG | MG |
| $C_{13}$ | F | F | F | F |
| $C_{14}$ | MG | MG | MG | MG |
| $C_{15}$ | G | G | MG | G |

Table 4.4d: Appropriateness rating of supplier alternative $\mathbf{S_4}$ with respect to the evaluation of criteria

| Criteria | Ratings expressed in linguistic terms given by the DMs | | | |
|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 |
| $C_1$ | G | G | G | G |
| $C_2$ | VG | G | G | MG |
| $C_3$ | G | MG | MG | G |
| $C_4$ | VG | VG | VG | VG |
| $C_5$ | MG | F | G | G |
| $C_6$ | G | G | G | MG |
| $C_7$ | VG | VG | G | VG |
| $C_8$ | G | G | G | G |
| $C_9$ | F | MG | MG | MG |
| $C_{10}$ | G | G | G | G |
| $C_{11}$ | G | MG | G | MG |
| $C_{12}$ | F | F | F | F |
| $C_{13}$ | MG | MG | G | G |
| $C_{14}$ | G | G | G | G |
| $C_{15}$ | VG | G | G | G |

Table 4.5: Aggregated fuzzy rating of supplier alternatives with respect to criteria: The initial decision making matrix

| Criteria | Aggregated fuzzy rating of supplier alternatives with respect to criteria | | | |
|---|---|---|---|---|
| | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
| $C_1$ | (0.1000,0.2000,0.2000,0.3000) | (0.4000,0.5250,0.5500,0.8000) | (0.4000,0.6000,0.6250,0.9000) | (0.7000,0.8000,0.8000,0.9000) |
| $C_2$ | (0.1000,0.3750,0.4000,0.6000) | (0.4000,0.5500,0.6000,0.8000) | (0.7000,0.8000,0.8000,0.9000) | (0.5000,0.7750,0.8250,1.0000) |
| $C_3$ | (0.1000,0.2500,0.3000,0.5000) | (0.2000,0.4500,0.4750,0.6000) | (0.5000,0.7000,0.7500,0.9000) | (0.5000,0.7000,0.7500,0.9000) |
| $C_4$ | (0.4000,0.5750,0.6500,0.8000) | (0.4000,0.5000,0.5000,0.6000) | (0.7000,0.8000,0.8000,0.9000) | (0.8000,0.9000,1.0000,1.0000) |
| $C_5$ | (0.2000,0.5000,0.5750,0.8000) | (0.4000,0.5500,0.6000,0.8000) | (0.4000,0.5750,0.6500,0.8000) | (0.4000,0.6750,0.7000,0.9000) |
| $C_6$ | (0.4000,0.5000,0.5000,0.6000) | (0.4000,0.5000,0.5000,0.6000) | (0.4000,0.5000,0.5000,0.6000) | (0.5000,0.7500,0.7750,0.9000) |
| $C_7$ | (0.4000,0.6750,0.7000,0.9000) | (0.2000,0.4500,0.4750,0.6000) | (0.5000,0.7500,0.7750,0.9000) | (0.7000,0.8750,0.9500,1.0000) |
| $C_8$ | (0.2000,0.4500,0.4750,0.6000) | (0.4000,0.6000,0.6250,0.9000) | (0.7000,0.8500,0.9000,1.0000) | (0.7000,0.8000,0.8000,0.9000) |
| $C_9$ | (0.4000,0.5000,0.5000,0.6000) | (0.2000,0.4500,0.4750,0.6000) | (0.7000,0.8000,0.8000,0.9000) | (0.4000,0.5750,0.6500,0.8000) |
| $C_{10}$ | (0.2000,0.4000,0.4500,0.6000) | (0.2000,0.3000,0.4000,0.5000) | (0.5000,0.7500,0.7750,0.9000) | (0.7000,0.8000,0.8000,0.9000) |
| $C_{11}$ | (0.4000,0.5500,0.6000,0.8000) | (0.2000,0.4000,0.4500,0.6000) | (0.5000,0.7000,0.7500,0.9000) | (0.5000,0.7000,0.7500,0.9000) |
| $C_{12}$ | (0.4000,0.5000,0.5000,0.6000) | (0.4000,0.5000,0.5000,0.6000) | (0.4000,0.5500,0.6000,0.8000) | (0.4000,0.5000,0.5000,0.6000) |
| $C_{13}$ | (0.2000,0.4500,0.4750,0.6000) | (0.4000,0.5500,0.6000,0.8000) | (0.4000,0.5000,0.5000,0.6000) | (0.5000,0.7000,0.7500,0.9000) |
| $C_{14}$ | (0.2000,0.4000,0.4500,0.6000) | (0.5000,0.6500,0.7250,0.9000) | (0.5000,0.6000,0.7000,0.8000) | (0.7000,0.8000,0.8000,0.9000) |
| $C_{15}$ | (0.4000,0.5000,0.5000,0.6000) | (0.4000,0.5500,0.6000,0.8000) | (0.5000,0.7500,0.7750,0.9000) | (0.7000,0.8250,0.8500,1.0000) |

Table 4.6: Aggregated fuzzy weight of criteria

| Criteria | Aggregated fuzzy weight |
|---|---|
| $C_1$ | (0.7000,0.8000,0.8000,0.9000) |
| $C_2$ | (0.7000,0.8500,0.9000,1.0000) |
| $C_3$ | (0.5000,0.7000,0.7500,0.9000) |
| $C_4$ | (0.7000,0.8000,0.8000,0.9000) |
| $C_5$ | (0.7000,0.8750,0.9500,1.0000) |
| $C_6$ | (0.5000,0.7500,0.7750,0.9000) |
| $C_7$ | (0.7000,0.8000,0.8000,0.9000) |
| $C_8$ | (0.5000,0.8000,0.8750,1.0000) |
| $C_9$ | (0.7000,0.8500,0.9000,1.0000) |
| $C_{10}$ | (0.7000,0.8000,0.8000,0.9000) |
| $C_{11}$ | (0.8000,0.9000,1.0000,1.0000) |
| $C_{12}$ | (0.7000,0.8500,0.9000,1.0000) |
| $C_{13}$ | (0.7000,0.8000,0.8000,0.9000) |
| $C_{14}$ | (0.5000,0.6500,0.7250,0.9000) |
| $C_{15}$ | (0.8000,0.9000,1.0000,1.0000) |

Table 4.7: Normalized decision matrix

| Criteria | Normalized fuzzy rating of supplier alternatives with respect to criteria | | | |
|---|---|---|---|---|
| | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
| $C_1$ | (0.1111,0.2222,0.2222,0.3333) | (0.4444,0.5833,0.6111,0.8889) | (0.4444,0.6667,0.6944,1.0000) | (0.7778,0.8889,0.8889,1.0000) |
| $C_2$ | (0.1000,0.3750,0.4000,0.6000) | (0.4000,0.5500,0.6000,0.8000) | (0.7000,0.8000,0.8000,0.9000) | (0.5000,0.7750,0.8250,1.0000) |
| $C_3$ | (0.1111,0.2778,0.3333,0.5556) | (0.2222,0.5000,0.5278,0.6667) | (0.5556,0.7778,0.8333,1.0000) | (0.5556,0.7778,0.8333,1.0000) |
| $C_4$ | (0.4000,0.5750,0.6500,0.8000) | (0.4000,0.5000,0.5000,0.6000) | (0.7000,0.8000,0.8000,0.9000) | (0.8000,0.9000,1.0000,1.0000) |
| $C_5$ | (0.2222,0.5556,0.6389,0.8889) | (0.4444,0.6111,0.6667,0.8889) | (0.4444,0.6389,0.7222,0.8889) | (0.4444,0.7500,0.7778,1.0000) |
| $C_6$ | (0.4444,0.5556,0.5556,0.6667) | (0.4444,0.5556,0.5556,0.6667) | (0.4444,0.5556,0.5556,0.6667) | (0.5556,0.8333,0.8611,1.0000) |
| $C_7$ | (0.4000,0.6750,0.7000,0.9000) | (0.2000,0.4500,0.4750,0.6000) | (0.5000,0.7500,0.7750,0.9000) | (0.7000,0.8750,0.9500,1.0000) |
| $C_8$ | (0.2000,0.4500,0.4750,0.6000) | (0.4000,0.6000,0.6250,0.9000) | (0.7000,0.8500,0.9000,1.0000) | (0.7000,0.8000,0.8000,0.9000) |
| $C_9$ | (0.4444,0.5556,0.5556,0.6667) | (0.2222,0.5000,0.5278,0.6667) | (0.7778,0.8889,0.8889,1.0000) | (0.4444,0.6389,0.7222,0.8889) |
| $C_{10}$ | (0.2222,0.4444,0.5000,0.6667) | (0.2222,0.3333,0.4444,0.5556) | (0.5556,0.8333,0.8611,1.0000) | (0.7778,0.8889,0.8889,1.0000) |
| $C_{11}$ | (0.4444,0.6111,0.6667,0.8889) | (0.2222,0.4444,0.5000,0.6667) | (0.5556,0.7778,0.8333,1.0000) | (0.5556,0.7778,0.8333,1.0000) |
| $C_{12}$ | (0.5000,0.6250,0.6250,0.7500) | (0.5000,0.6250,0.6250,0.7500) | (0.5000,0.6875,0.7500,1.0000) | (0.5000,0.6250,0.6250,0.7500) |
| $C_{13}$ | (0.2222,0.5000,0.5278,0.6667) | (0.4444,0.6111,0.6667,0.8889) | (0.4444,0.5556,0.5556,0.6667) | (0.5556,0.7778,0.8333,1.0000) |
| $C_{14}$ | (0.2222,0.4444,0.5000,0.6667) | (0.5556,0.7222,0.8056,1.0000) | (0.5556,0.6667,0.7778,0.8889) | (0.7778,0.8889,0.8889,1.0000) |
| $C_{15}$ | (0.4000,0.5000,0.5000,0.6000) | (0.4000,0.5500,0.6000,0.8000) | (0.5000,0.7500,0.7750,0.9000) | (0.7000,0.8250,0.8500,1.0000) |

Table 4.8: Weighted normalized decision matrix

| Criteria | Weighted normalized rating of supplier alternatives with respect to criteria | | | |
|---|---|---|---|---|
| | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
| $C_1$ | (0.0778,0.1778,0.1778,0.3000) | (0.3111,0.4667,0.4889,0.8000) | (0.3111,0.5333,0.5556,0.9000) | (0.5444,0.7111,0.7111,0.9000) |
| $C_2$ | (0.0700,0.3188,0.3600,0.6000) | (0.2800,0.4675,0.5400,0.8000) | (0.4900,0.6800,0.7200,0.9000) | (0.3500,0.6588,0.7425,1.0000) |
| $C_3$ | (0.0556,0.1944,0.2500,0.5000) | (0.1111,0.3500,0.3958,0.6000) | (0.2778,0.5444,0.6250,0.9000) | (0.2778,0.5444,0.6250,0.9000) |
| $C_4$ | (0.2800,0.4600,0.5200,0.7200) | (0.2800,0.4000,0.4000,0.5400) | (0.4900,0.6400,0.6400,0.8100) | (0.5600,0.7200,0.8000,0.9000) |
| $C_5$ | (0.1556,0.4861,0.6069,0.8889) | (0.3111,0.5347,0.6333,0.8889) | (0.3111,0.5590,0.6861,0.8889) | (0.3111,0.6563,0.7389,1.0000) |
| $C_6$ | (0.2222,0.4167,0.4306,0.6000) | (0.2222,0.4167,0.4306,0.6000) | (0.2222,0.4167,0.4306,0.6000) | (0.2778,0.6250,0.6674,0.9000) |
| $C_7$ | (0.2800,0.5400,0.5600,0.8100) | (0.1400,0.3600,0.3800,0.5400) | (0.3500,0.6000,0.6200,0.8100) | (0.4900,0.7000,0.7600,0.9000) |
| $C_8$ | (0.1000,0.3600,0.4156,0.6000) | (0.2000,0.4800,0.5469,0.9000) | (0.3500,0.6800,0.7875,1.0000) | (0.3500,0.6400,0.7000,0.9000) |
| $C_9$ | (0.3111,0.4722,0.5000,0.6667) | (0.1556,0.4250,0.4750,0.6667) | (0.5444,0.7556,0.8000,1.0000) | (0.3111,0.5431,0.6500,0.8889) |
| $C_{10}$ | (0.1556,0.3556,0.4000,0.6000) | (0.1556,0.2667,0.3556,0.5000) | (0.3889,0.6667,0.6889,0.9000) | (0.5444,0.7111,0.7111,0.9000) |
| $C_{11}$ | (0.3556,0.5500,0.6667,0.8889) | (0.1778,0.4000,0.5000,0.6667) | (0.4444,0.7000,0.8333,1.0000) | (0.4444,0.7000,0.8333,1.0000) |
| $C_{12}$ | (0.3500,0.5313,0.5625,0.7500) | (0.3500,0.5313,0.5625,0.7500) | (0.3500,0.5844,0.6750,1.0000) | (0.3500,0.5313,0.5625,0.7500) |
| $C_{13}$ | (0.1556,0.4000,0.4222,0.6000) | (0.3111,0.4889,0.5333,0.8000) | (0.3111,0.4444,0.4444,0.6000) | (0.3889,0.6222,0.6667,0.9000) |
| $C_{14}$ | (0.1111,0.2889,0.3625,0.6000) | (0.2778,0.4694,0.5840,0.9000) | (0.2778,0.4333,0.5639,0.8000) | (0.3889,0.5778,0.6444,0.9000) |
| $C_{15}$ | (0.3200,0.4500,0.5000,0.6000) | (0.3200,0.4950,0.6000,0.8000) | (0.4000,0.6750,0.7750,0.9000) | (0.5600,0.7425,0.8500,1.0000) |

Table 4.9: Partial matrices of dominance: Exploration of fuzzy distance formula

| Criteria | Dominance between the alternatives (with respect to individual criterion) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $[S_1,S_2]$ | $[S_1,S_3]$ | $[S_1,S_4]$ | $[S_2,S_1]$ | $[S_2,S_3]$ | $[S_2,S_4]$ | $[S_3,S_1]$ | $[S_3,S_2]$ | $[S_3,S_4]$ | $[S_4,S_1]$ | $[S_4,S_2]$ | $[S_4,S_3]$ |
| $C_1$ | -0.3481 | -0.4134 | -0.5354 | 0.3481 | -0.0687 | -0.2083 | 0.4134 | 0.0687 | -0.1660 | 0.5354 | 0.3643 | 0.1660 |
| $C_2$ | -0.1862 | -0.3628 | -0.3537 | 0.1862 | -0.1814 | -0.1750 | 0.3628 | 0.1814 | 0.0874 | 0.3537 | 0.3447 | -0.0874 |
| $C_3$ | -0.1210 | -0.3437 | -0.3437 | 0.1210 | -0.2281 | -0.2281 | 0.3437 | 0.2281 | 0.0000 | 0.3437 | 0.4327 | 0.0000 |
| $C_4$ | 0.1122 | -0.1573 | -0.2534 | -0.1122 | -0.2409 | -0.3429 | 0.1573 | 0.2409 | -0.1061 | 0.2534 | 0.6416 | 0.1061 |
| $C_5$ | -0.0825 | -0.0946 | -0.1440 | 0.0825 | -0.0291 | -0.0978 | 0.0946 | 0.0291 | -0.0784 | 0.1440 | 0.1956 | 0.0784 |
| $C_6$ | 0.0000 | 0.0000 | -0.2194 | 0.0000 | 0.0000 | -0.2194 | 0.0000 | 0.0000 | -0.2194 | 0.2194 | 0.4362 | 0.2194 |
| $C_7$ | 0.1983 | -0.0550 | -0.1716 | -0.1983 | -0.2409 | -0.3578 | 0.0550 | 0.2409 | -0.1197 | 0.1716 | 0.6482 | 0.1197 |
| $C_8$ | -0.1814 | -0.3403 | -0.2792 | 0.1814 | -0.1806 | -0.1337 | 0.3403 | 0.1806 | 0.0694 | 0.2792 | 0.2338 | -0.0694 |
| $C_9$ | 0.0822 | -0.2898 | -0.1387 | -0.0822 | -0.3454 | -0.1719 | 0.2898 | 0.3454 | 0.1833 | 0.1387 | 0.3162 | -0.1833 |
| $C_{10}$ | 0.0705 | -0.2849 | -0.3408 | -0.0705 | -0.3484 | -0.3985 | 0.2849 | 0.3484 | -0.0816 | 0.3408 | 0.7223 | 0.0816 |
| $C_{11}$ | 0.1812 | -0.1328 | -0.1328 | -0.1812 | -0.3096 | -0.3096 | 0.1328 | 0.3096 | 0.0000 | 0.1328 | 0.5745 | 0.0000 |
| $C_{12}$ | 0.0000 | -0.1396 | 0.0000 | 0.0000 | -0.1396 | 0.0000 | 0.1396 | 0.1396 | 0.1396 | 0.0000 | 0.0000 | -0.1396 |
| $C_{13}$ | -0.1453 | -0.0816 | -0.2518 | 0.1453 | 0.1117 | -0.1136 | 0.0816 | -0.1117 | -0.2104 | 0.2518 | 0.2170 | 0.2104 |
| $C_{14}$ | -0.2233 | -0.1797 | -0.2873 | 0.2233 | 0.0541 | -0.0833 | 0.1797 | -0.0541 | -0.1115 | 0.2873 | 0.1359 | 0.1115 |
| $C_{15}$ | -0.1140 | -0.2359 | -0.3262 | 0.1140 | -0.1409 | -0.2352 | 0.2359 | 0.1409 | -0.1070 | 0.3262 | 0.4221 | 0.1070 |
| Total | -0.7574 | -3.1115 | -3.7778 | 0.7574 | -2.2879 | -3.0751 | 3.1115 | 2.2879 | -0.7203 | 3.7778 | 5.6851 | 0.7203 |

Table 4.10: Final matrices of dominance

| Alternatives | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
|---|---|---|---|---|
| $S_1$ | 0.0000 | -0.7574 | -3.1115 | -3.7778 |
| $S_2$ | 0.7574 | 0.0000 | -2.2879 | -3.0751 |
| $S_3$ | 3.1115 | 2.2879 | 0.0000 | -0.7203 |
| $S_4$ | 3.7778 | 5.6851 | 0.7203 | 0.0000 |

Table 4.11: Global dominance value and corresponding ranking order

| Alternatives | $\delta$ | $\xi$ | Ranking order |
|---|---|---|---|
| $S_1$ | -7.6466 | 0.000 | 4 |
| $S_2$ | -4.6056 | 0.171 | 3 |
| $S_3$ | 4.6790 | 0.691 | 2 |
| $S_4$ | 10.1832 | 1.000 | 1 |

Table 4.12: Partial matrices of dominance: Exploration of fuzzy subtraction rule

| Criteria | $[S_1,S_2]$ | $[S_1,S_3]$ | $[S_1,S_4]$ | $[S_2,S_1]$ | $[S_2,S_3]$ | $[S_2,S_4]$ |
|---|---|---|---|---|---|---|
| $C_1$ | (-0.7222,-0.3111,-0.2889,-0.0111) | (-0.8222,-0.3778,-0.3556,-0.0111) | (-0.8222,-0.5333,-0.5333,-0.2444) | (0.0111,0.2889,0.3111,0.7222) | (-0.5889,-0.0889,-0.0444,0.4889) | (-0.5889,-0.2444,-0.2222,0.2556) |
| $C_2$ | (-0.7300,-0.2213,-0.1075,0.3200) | (-0.8300,-0.4013,-0.3200,0.1100) | (-0.9300,-0.4238,-0.2988,0.2500) | (-0.3200,0.1075,0.2213,0.7300) | (-0.6200,-0.2525,-0.1400,0.3100) | (-0.7200,-0.2750,-0.1188,0.4500) |
| $C_3$ | (-0.5444,-0.2014,-0.1000,0.3889) | (-0.8444,-0.4306,-0.2944,0.2222) | (-0.8444,-0.4306,-0.2944,0.2222) | (-0.3889,0.1000,0.2014,0.5444) | (-0.7889,-0.2750,-0.1486,0.3222) | (-0.7889,-0.2750,-0.1486,0.3222) |
| $C_4$ | (-0.2600,0.0600,0.1200,0.4400) | (-0.5300,-0.1800,-0.1200,0.2300) | (-0.6200,-0.3400,-0.2000,0.1600) | (-0.4400,-0.1200,-0.0600,0.2600) | (-0.5300,-0.2400,-0.2400,0.0500) | (-0.6200,-0.4000,-0.3200,-0.0200) |
| $C_5$ | (-0.7333,-0.1472,0.0722,0.5778) | (-0.7333,-0.2000,0.0479,0.5778) | (-0.8444,-0.2528,-0.0493,0.5778) | (-0.5778,-0.0722,0.1472,0.7333) | (-0.5778,-0.1514,0.0743,0.5778) | (-0.6889,-0.2042,-0.0229,0.5778) |
| $C_6$ | (-0.3778,-0.0139,0.0139,0.3778) | (-0.3778,-0.0139,0.0139,0.3778) | (-0.6778,-0.2507,-0.1944,0.3222) | (-0.3778,-0.0139,0.0139,0.3778) | (-0.3778,-0.0139,0.0139,0.3778) | (-0.6778,-0.2507,-0.1944,0.3222) |
| $C_7$ | (-0.2600,0.1600,0.2000,0.6700) | (-0.5300,-0.0800,-0.0400,0.4600) | (-0.6200,-0.2200,-0.1400,0.3200) | (-0.6700,-0.2000,-0.1600,0.2600) | (-0.6700,-0.2600,-0.2200,0.1900) | (-0.7600,-0.4000,-0.3200,0.0500) |
| $C_8$ | (-0.8000,-0.1869,-0.0644,0.4000) | (-0.9000,-0.4275,-0.2644,0.2500) | (-0.8000,-0.3400,-0.2244,0.2500) | (-0.4000,0.0644,0.1869,0.8000) | (-0.8000,-0.3075,-0.1331,0.5500) | (-0.7000,-0.2200,-0.0931,0.5500) |
| $C_9$ | (-0.3556,-0.0028,0.0750,0.5111) | (-0.6889,-0.3278,-0.2556,0.1222) | (-0.5778,-0.1778,-0.0431,0.3556) | (-0.5111,-0.0750,0.0028,0.3556) | (-0.8444,-0.3750,-0.2806,0.1222) | (-0.7333,-0.2250,-0.0681,0.3556) |
| $C_{10}$ | (-0.3444,0.0000,0.1333,0.4444) | (-0.7444,-0.3333,-0.2667,0.2111) | (-0.7444,-0.3556,-0.3111,0.0556) | (-0.4444,-0.1333,0.0000,0.3444) | (-0.7444,-0.4222,-0.3111,0.1111) | (-0.7444,-0.4444,-0.3556,-0.0444) |
| $C_{11}$ | (-0.3111,0.0500,0.2667,0.7111) | (-0.6444,-0.2833,-0.0333,0.4444) | (-0.6444,-0.2833,-0.0333,0.4444) | (-0.7111,-0.2667,-0.0500,0.3111) | (-0.8222,-0.4333,-0.2000,0.2222) | (-0.8222,-0.4333,-0.2000,0.2222) |
| $C_{12}$ | (-0.4000,-0.0313,0.0313,0.4000) | (-0.6500,-0.1438,-0.0219,0.4000) | (-0.4000,-0.0313,0.0313,0.4000) | (-0.4000,-0.0313,0.0313,0.4000) | (-0.6500,-0.1438,-0.0219,0.4000) | (-0.4000,-0.0313,0.0313,0.4000) |
| $C_{13}$ | (-0.6444,-0.1333,-0.0667,0.2889) | (-0.4444,-0.0444,-0.0222,0.2889) | (-0.7444,-0.2667,-0.2000,0.2111) | (-0.2889,0.0667,0.1333,0.6444) | (-0.2889,0.0444,0.0889,0.4889) | (-0.5889,-0.1778,-0.0889,0.4111) |
| $C_{14}$ | (-0.7889,-0.2951,-0.1069,0.3222) | (-0.6889,-0.2750,-0.0708,0.3222) | (-0.7889,-0.3556,-0.2153,0.2111) | (-0.3222,0.1069,0.2951,0.7889) | (-0.5222,-0.0944,0.1507,0.6222) | (-0.6222,-0.1750,0.0062,0.5111) |
| $C_{15}$ | (-0.4800,-0.1500,0.0050,0.2800) | (-0.5800,-0.3250,-0.1750,0.2000) | (-0.6800,-0.4000,-0.2425,0.0400) | (-0.2800,-0.0050,0.1500,0.4800) | (-0.5800,-0.2800,-0.0750,0.4000) | (-0.6800,-0.3550,-0.1425,0.2400) |

Table 4.12 (continued): Partial matrices of dominance: Exploration of fuzzy subtraction rule

| Criteria | $[S_3,S_1]$ | $[S_3,S_2]$ | $[S_3,S_4]$ | $[S_4,S_1]$ | $[S_4,S_2]$ | $[S_4,S_3]$ |
|---|---|---|---|---|---|---|
| $C_1$ | (0.0111,0.3556,0.3778,0.8222) | (-0.4889,0.0444,0.0889,0.5889) | (-0.5889,-0.1778,-0.1556,0.3556) | (0.2444,0.5333,0.5333,0.8222) | (-0.2556,0.2222,0.2444,0.5889) | (-0.3556,0.1556,0.1778,0.5889) |
| $C_2$ | (-0.1100,0.3200,0.4013,0.8300) | (-0.3100,0.1400,0.2525,0.6200) | (-0.5100,-0.0625,0.0612,0.5500) | (-0.2500,0.2988,0.4238,0.9300) | (-0.4500,0.1188,0.2750,0.7200) | (-0.5500,-0.0612,0.0625,0.5100) |
| $C_3$ | (-0.2222,0.2944,0.4306,0.8444) | (-0.3222,0.1486,0.2750,0.7889) | (-0.6222,-0.0806,0.0806,0.6222) | (-0.2222,0.2944,0.4306,0.8444) | (-0.3222,0.1486,0.2750,0.7889) | (-0.6222,-0.0806,0.0806,0.6222) |
| $C_4$ | (-0.2300,0.1200,0.1800,0.5300) | (-0.0500,0.2400,0.2400,0.5300) | (-0.4100,-0.1600,-0.0800,0.2500) | (-0.1600,0.2000,0.3400,0.6200) | (0.0200,0.3200,0.4000,0.6200) | (-0.2500,0.0800,0.1600,0.4100) |
| $C_5$ | (-0.5778,-0.0479,0.2000,0.7333) | (-0.5778,-0.0743,0.1514,0.5778) | (-0.6889,-0.1799,0.0299,0.5778) | (-0.5778,0.0493,0.2528,0.8444) | (-0.5778,0.0229,0.2042,0.6889) | (-0.5778,-0.0299,0.1799,0.6889) |
| $C_6$ | (-0.3778,-0.0139,0.0139,0.3778) | (-0.3778,-0.0139,0.0139,0.3778) | (-0.6778,-0.2507,-0.1944,0.3222) | (-0.3222,0.1944,0.2507,0.6778) | (-0.3222,0.1944,0.2507,0.6778) | (-0.3222,0.1944,0.2507,0.6778) |
| $C_7$ | (-0.4600,0.0400,0.0800,0.5300) | (-0.1900,0.2200,0.2600,0.6700) | (-0.5500,-0.1600,-0.0800,0.3200) | (-0.3200,0.1400,0.2200,0.6200) | (-0.0500,0.3200,0.4000,0.7600) | (-0.3200,0.0800,0.1600,0.5500) |
| $C_8$ | (-0.2500,0.2644,0.4275,0.9000) | (-0.5500,0.1331,0.3075,0.8000) | (-0.5500,-0.0200,0.1475,0.6500) | (-0.2500,0.2244,0.3400,0.8000) | (-0.5500,0.0931,0.2200,0.7000) | (-0.6500,-0.1475,0.0200,0.5500) |
| $C_9$ | (-0.1222,0.2556,0.3278,0.6889) | (-0.1222,0.2806,0.3750,0.8444) | (-0.3444,0.1056,0.2569,0.6889) | (-0.3556,0.0431,0.1778,0.5778) | (-0.3556,0.0681,0.2250,0.7333) | (-0.6889,-0.2569,-0.1056,0.3444) |
| $C_{10}$ | (-0.2111,0.2667,0.3333,0.7444) | (-0.1111,0.3111,0.4222,0.7444) | (-0.5111,-0.0444,-0.0222,0.3556) | (-0.0556,0.3111,0.3556, 0.7444) | (0.0444,0.3556,0.4444,0.7444) | (-0.3556,0.0222,0.0444,0.5111) |
| $C_{11}$ | (-0.4444,0.0333,0.2833,0.6444) | (-0.2222,0.2000,0.4333,0.8222) | (-0.5556,-0.1333,0.1333,0.5556) | (-0.4444,0.0333,0.2833,0.6444) | (-0.2222,0.2000,0.4333,0.8222) | (-0.5556,-0.1333,0.1333,0.5556) |
| $C_{12}$ | (-0.4000,0.0219,0.1438,0.6500) | (-0.4000,0.0219,0.1438,0.6500) | (-0.4000,0.0219,0.1438,0.6500) | (-0.4000,-0.0313,0.0313,0.4000) | (-0.4000,-0.0313,0.0313,0.4000) | (-0.6500,-0.1438,-0.0219,0.4000) |
| $C_{13}$ | (-0.2889,0.0222,0.0444,0.4444) | (-0.4889,-0.0889,-0.0444,0.2889) | (-0.5889,-0.2222,-0.1778,0.2111) | (-0.2111,0.2000,0.2667,0.7444) | (-0.4111,0.0889,0.1778,0.5889) | (-0.2111,0.1778,0.2222,0.5889) |
| $C_{14}$ | (-0.3222,0.0708,0.2750,0.6889) | (-0.6222,-0.1507,0.0944,0.5222) | (-0.6222,-0.2111,-0.0139,0.4111) | (-0.2111,0.2153,0.3556,0.7889) | (-0.5111,-0.0062,0.1750,0.6222) | (-0.4111,0.0139,0.2111,0.6222) |
| $C_{15}$ | (-0.2000,0.1750,0.3250,0.5800) | (-0.4000,0.0750,0.2800,0.5800) | (-0.6000,-0.1750,0.0325,0.3400) | (-0.0400,0.2425,0.4000,0.6800) | (-0.2400,0.1425,0.3550,0.6800) | (-0.3400,-0.0325,0.1750,0.6000) |

Table 4.13: Final matrices of dominance

| Alternatives | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
|---|---|---|---|---|
| $S_1$ | (0.0000,0.0000,0.0000,0.0000) | (-7.7522,-1.4242,0.1830,6.1211) | (-10.0089,-3.8436,-2.1781,4.2056) | (-10.7389,-4.6613,-2.9487,3.5756) |
| $S_2$ | (-6.1211,-0.1830,1.4242,7.7522) | (0.0000,0.0000,0.0000,0.0000) | (-9.4056,-3.2935,-1.4869,5.2333) | (-10.1356,-4.1111,-2.2576,4.6033) |
| $S_3$ | (-4.2056,2.1781,3.8436,10.0089) | (-5.2333,1.4869,3.2935,9.4056) | (0.0000,0.0000,0.0000,0.0000) | (-8.2200, -1.7501, 0.1618, 6.8600) |
| $S_4$ | (-3.5756,2.9487,4.6613,10.7389) | (-4.6033,2.2576,4.1111,10.1356) | (-6.8600,-0.1618,1.7501,8.2200) | (0.0000, 0.0000, 0.0000, 0.0000) |

Table 4.14: Global dominance measure, corresponding crisp score, normalized crisp score and supplier ranking order

| Alternatives | $\delta$ (in terms of fuzzy number) | Defuzzified $(\delta)$ | $\xi$ | Ranking order |
|---|---|---|---|---|
| $S_1$ | (-28.5000,-9.9291,-4.9438,13.9022) | -7.3677 | 0.0000 | 4 |
| $S_2$ | (-25.6622,-7.5876,-2.3203,17.5889) | -4.4953 | 0.1944 | 3 |
| $S_3$ | (-17.6589,1.9149, 7.2989, 26.2744) | 4.4573 | 0.8004 | 2 |
| $S_4$ | (-15.0389,5.0444,10.5224,29.0944) | 7.4056 | 1.0000 | 1 |

Table 4.15: Separation measure of each alternative with respect to ideal $\left(d_i^+\right)$ and anti-ideal solution $\left(d_i^-\right)$: Computation of closeness coefficient $\left(CC_i\right)$ and corresponding ranking order

| Alternatives | $d_i^+$ | $d_i^-$ | $CC_i$ | Ranking order (by Fuzzy-TOPSIS) |
|---|---|---|---|---|
| $S_1$ | 9.0074 | 6.8355 | 0.431455 | 4 |
| $S_2$ | 8.3640 | 7.5464 | 0.474306 | 3 |
| $S_3$ | 6.3521 | 9.7190 | 0.60475 | 2 |
| $S_4$ | 5.6693 | 10.4437 | 0.648154 | 1 |

Table 4.16: Ranking order of alternative suppliers based on $S_i$, $R_i$ and $Q_i$

| Alternatives | Utility measure $S_i$ | Ranking order | Regret measure $R_i$ | Ranking order | $\tilde{Q}_i$ | $Q_i$ | Ranking order (by Fuzzy-VIKOR) |
|---|---|---|---|---|---|---|---|
| $S_1$ | 6.355 | 4 | 0.635 | 4 | (0.784,0.968,1.035,1.247) | 1.008 | 4 |
| $S_2$ | 5.693 | 3 | 0.550 | 3 | (0.727,0.733,0.755,0.678) | 0.723 | 3 |
| $S_3$ | 3.593 | 2 | 0.395 | 1 | (0.079,0.097,0.113,0.120) | 0.102 | 2 |
| $S_4$ | 2.894 | 1 | 0.424 | 2 | (0.000,0.052,0.104,0.0910 | 0.062 | 1 |

Table 4.17: Pertinent attributes relevant to g-resilient supplier selection

| Performance dimensions/ main-criteria, $PD_j$ | Sub-criteria $(C_{jl})$ |
|---|---|
| Green performance, $PD_1$ | Use of environment friendly technology, $C_{11}$ |
| | Use of environment friendly materials, $C_{12}$ |
| | Green market share, $C_{13}$ |
| | Partnership with green organizations, $C_{14}$ |
| | Management commitment, $C_{15}$ |
| | Adherence to environmental policies, $C_{16}$ |
| | Green R & D projects, $C_{17}$ |
| | Staff Training, $C_{18}$ |
| | Lean process planning, $C_{19}$ |
| | Design for environment, $C_{1,10}$ |
| | Environmental certification, $C_{1,11}$ |
| | Pollution control initiatives, $C_{1,12}$ |
| Resilience performance, $PD_2$ | Investment in capacity buffers, $C_{21}$ |
| | Responsiveness, $C_{22}$ |
| | Capacity for holding strategic inventory stocks for crises, $C_{23}$ |

Table 4.18: Weight of g-resilient performance dimensions expressed in linguistic terms as given by the DMs: Corresponding aggregated fuzzy weight

| Performance dimensions | Linguistic weights as given by the DMs | | | | Aggregated fuzzy weight |
|---|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 | |
| $PD_1$ | VH | H | VH | H | (0.7000,0.8500,0.9000,1.0000) |
| $PD_2$ | VH | VH | VH | H | (0.7000,0.8750,0.9500,1.0000) |

Table 4.19: Computed fuzzy rating of g-resilient performance dimensions

| Performance dimensions $(PD_j)$ | Computed fuzzy rating $(\tilde{x}_{ij})$ of alternative suppliers with respect to g-resilient performance dimensions | | | |
|---|---|---|---|---|
| | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
| $PD_1$ | (0.1939,0.4382,0.5150,0.9278) | (0.2175,0.4591,0.5389,0.9658) | (0.3693,0.6659,0.7637,1.2519) | (0.3921,0.7010,0.8077,1.2835) |
| $PD_2$ | (0.2000,0.4238,0.5133,0.8400) | (0.3036,0.5376,0.6832,1.1650) | (0.3321,0.5802,0.7160,1.0800) | (0.4500,0.7218,0.8638,1.3100) |

Table 4.20: Computed fuzzy g-resilient index of alternative suppliers and corresponding ranking order

| Alternatives | $GRI_i$ | Defuzzified value | Ranking order |
|---|---|---|---|
| $S_1$ | (0.1379,0.4017,0.5514,1.2627) | 0.588436 | 4 |
| $S_2$ | (0.1824,0.4652,0.6575,1.522) | 0.706778 | 3 |
| $S_3$ | (0.2455,0.5804,0.7927,1.6656) | 0.821066 | 2 |
| $S_4$ | (0.2947,0.6635,0.8972,1.8525) | 0.926977 | 1 |

Table 4.21: Determination of FPII and ranking order of criteria based on performance (for alternative suppliers)

| Criteria | S1 | | | S2 | | |
|---|---|---|---|---|---|---|
| | FPII | Defuzzified FPII | Criteria ranking order | FPII | Defuzzified FPII | Criteria ranking order |
| C11 | (0.0300,0.0400,0.0400,0.0300) | 0.0350 | 12 | (0.1200,0.1050,0.1100,0.0800) | 0.1038 | 4 |
| C12 | (0.0300,0.0563,0.0400,0.0000) | 0.0316 | 15 | (0.1200,0.0825,0.0600,0.0000) | 0.0656 | 9 |
| C13 | (0.0500,0.0750,0.0750,0.0500) | 0.0625 | 7 | (0.1000,0.1350,0.1188,0.0600) | 0.1034 | 5 |
| C14 | (0.1200,0.1150,0.1300,0.0800) | 0.1113 | 3 | (0.1200,0.1000,0.1000,0.0600) | 0.0950 | 7 |
| C15 | (0.0600,0.0625,0.0288,0.0000) | 0.0378 | 11 | (0.1200,0.0688,0.0300,0.0000) | 0.0547 | 12 |
| C16 | (0.2000,0.1250,0.1125,0.0600) | 0.1244 | 1 | (0.2000,0.1250,0.1125,0.0600) | 0.1244 | 2 |
| C17 | (0.1200,0.1350,0.1400,0.0900) | 0.1213 | 2 | (0.0600,0.0900,0.0950,0.0600) | 0.0763 | 8 |
| C18 | (0.1000,0.0900,0.0594,0.0000) | 0.0623 | 8 | (0.2000,0.1200,0.0781,0.0000) | 0.0995 | 6 |
| C19 | (0.1200,0.0750,0.0500,0.0000) | 0.0613 | 9 | (0.0600,0.0675,0.0475,0.0000) | 0.0438 | 13 |
| C1,10 | (0.0600,0.0800,0.0900,0.0600) | 0.0725 | 6 | (0.0600,0.0600,0.0800,0.0500) | 0.0625 | 10 |
| C1,11 | (0.0800,0.0550,0.0000,0.0000) | 0.0338 | 13 | (0.0400,0.0400,0.0000,0.0000) | 0.0200 | 15 |
| C1,12 | (0.1200,0.0750,0.0500,0.0000) | 0.0613 | 9 | (0.1200,0.0750,0.0500,0.0000) | 0.0613 | 11 |
| C21 | (0.0600,0.0900,0.0950,0.0600) | 0.0763 | 5 | (0.1200,0.1100,0.1200,0.0800) | 0.1075 | 3 |
| C22 | (0.1000,0.1400,0.1238,0.0600) | 0.1059 | 4 | (0.2500,0.2275,0.1994,0.0900) | 0.1917 | 1 |
| C23 | (0.0800,0.0500,0.0000,0.0000) | 0.0325 | 14 | (0.0800,0.0550,0.0000,0.0000) | 0.0338 | 14 |

Table 4.21 (continued): Determination of FPII and ranking order of criteria based on performance (for alternative suppliers)

| Criteria | S3 | | | S4 | | |
|---|---|---|---|---|---|---|
| | FPII | Defuzzified FPII | Criteria ranking order | FPII | Defuzzified FPII | Criteria ranking order |
| C11 | (0.1200,0.1200,0.1250,0.0900) | 0.1138 | 8 | (0.2100,0.1600,0.1600,0.0900) | 0.1550 | 6 |
| C12 | (0.2100,0.1200,0.0800,0.0000) | 0.1025 | 9 | (0.1500,0.1163,0.0825,0.0000) | 0.0872 | 10 |
| C13 | (0.2500,0.2100,0.1875,0.0900) | 0.1844 | 1 | (0.2500,0.2100,0.1875,0.0900) | 0.1844 | 2 |
| C14 | (0.2100,0.1600,0.1600,0.0900) | 0.1550 | 4 | (0.2400,0.1800,0.2000,0.1000) | 0.1800 | 3 |
| C15 | (0.1200,0.0719,0.0325,0.0000) | 0.0561 | 13 | (0.1200,0.0844,0.0350,0.0000) | 0.0598 | 13 |
| C16 | (0.2000,0.1250,0.1125,0.0600) | 0.1244 | 7 | (0.2500,0.1875,0.1744,0.0900) | 0.1755 | 4 |
| C17 | (0.1500,0.1500,0.1550,0.0900) | 0.1363 | 5 | (0.2100,0.1750,0.1900,0.1000) | 0.1688 | 5 |
| C18 | (0.3500,0.1700,0.1125,0.0000) | 0.1581 | 3 | (0.3500,0.1600,0.1000,0.0000) | 0.1525 | 8 |
| C19 | (0.2100,0.1200,0.0800,0.0000) | 0.1025 | 9 | (0.1200,0.0863,0.0650,0.0000) | 0.0678 | 11 |
| C1,10 | (0.1500,0.1500,0.1550,0.0900) | 0.1363 | 6 | (0.2100,0.1600,0.1600,0.0900) | 0.1550 | 6 |
| C1,11 | (0.1000,0.0700,0.0000,0.0000) | 0.0425 | 15 | (0.1000,0.0700,0.0000,0.0000) | 0.0425 | 15 |
| C1,12 | (0.1200,0.0825,0.0600,0.0000) | 0.0656 | 12 | (0.1200,0.0750,0.0500,0.0000) | 0.0613 | 12 |
| C21 | (0.1200,0.1000,0.1000,0.0600) | 0.0950 | 11 | (0.1500,0.1400,0.1500,0.0900) | 0.1325 | 9 |
| C22 | (0.2500,0.2100,0.1925,0.0800) | 0.1831 | 2 | (0.3500,0.2800,0.2200,0.0900) | 0.2350 | 1 |
| C23 | (0.1000,0.0750,0.0000,0.0000) | 0.0438 | 14 | (0.1400,0.0825,0.0000,0.0000) | 0.0556 | 14 |

Table 4.22: Computation of crisp weight and relative weight of criteria

| Criteria | Crisp weight | Relative weight $(w_{rc})$ |
|---|---|---|
| $C_1$ | 0.800 | 0.865 |
| $C_2$ | 0.863 | 0.932 |
| $C_3$ | 0.713 | 0.770 |
| $C_4$ | 0.800 | 0.865 |
| $C_5$ | 0.881 | 0.953 |
| $C_6$ | 0.731 | 0.791 |
| $C_7$ | 0.800 | 0.865 |
| $C_8$ | 0.794 | 0.858 |
| $C_9$ | 0.863 | 0.932 |
| $C_{10}$ | 0.800 | 0.865 |
| $C_{11}$ | 0.925 | 1.000 |
| $C_{12}$ | 0.863 | 0.932 |
| $C_{13}$ | 0.800 | 0.865 |
| $C_{14}$ | 0.694 | 0.750 |
| $C_{15}$ | 0.925 | 1.000 |

Table 4.23: Partial matrices of dominance

| Criteria | Dominance for all possible combination of alternative pairs with respect to criteria | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $[S_1, S_2]$ | $[S_1,S_3]$ | $[S_1,S_4]$ | $[S_2,S_1]$ | $[S_2,S_3]$ | $[S_2,S_4]$ | $[S_3,S_1]$ | $[S_3,S_2]$ | $[S_3,S_4]$ | $[S_4,S_1]$ | $[S_4,S_2]$ | $[S_4,S_3]$ |
| $C_1$ | -3.470 | -3.804 | -4.290 | 0.227 | -1.575 | -2.651 | 0.248 | 0.103 | -2.279 | 0.280 | 0.173 | 0.149 |
| $C_2$ | -2.276 | -3.201 | -3.232 | 0.160 | -2.284 | -2.321 | 0.225 | 0.161 | 0.101 | 0.228 | 0.163 | -1.439 |
| $C_3$ | -2.347 | -3.855 | -3.855 | 0.137 | -3.092 | -3.092 | 0.224 | 0.180 | 0.000 | 0.224 | 0.180 | 0.000 |
| $C_4$ | 0.131 | -2.231 | -2.915 | -1.999 | -2.878 | -3.458 | 0.146 | 0.188 | -1.957 | 0.190 | 0.226 | 0.128 |
| $C_5$ | -1.330 | -1.500 | -1.994 | 0.096 | -0.929 | -1.707 | 0.108 | 0.067 | -1.522 | 0.143 | 0.123 | 0.109 |
| $C_6$ | 0.000 | 0.000 | -2.990 | 0.000 | 0.000 | -2.990 | 0.000 | 0.000 | -2.990 | 0.178 | 0.178 | 0.178 |
| $C_7$ | 0.171 | -1.340 | -2.372 | -2.621 | -2.878 | -3.484 | 0.088 | 0.188 | -1.985 | 0.155 | 0.228 | 0.130 |
| $C_8$ | -2.424 | -3.403 | -3.086 | 0.157 | -2.525 | -2.170 | 0.221 | 0.164 | 0.099 | 0.200 | 0.141 | 0.099 |
| $C_9$ | 0.095 | -2.921 | -2.030 | -1.345 | -3.120 | -2.213 | 0.206 | 0.220 | 0.159 | 0.143 | 0.156 | -2.265 |
| $C_{10}$ | 0.104 | -3.151 | -3.350 | -1.598 | -3.512 | -3.678 | 0.206 | 0.229 | -1.396 | 0.219 | 0.240 | 0.091 |
| $C_{11}$ | 0.161 | -1.878 | -1.878 | -2.130 | -2.821 | -2.821 | 0.142 | 0.213 | 0.000 | 0.142 | 0.213 | 0.000 |
| $C_{12}$ | 0.000 | -2.017 | 0.000 | 0.000 | -2.017 | 0.000 | 0.142 | 0.142 | 0.142 | 0.000 | 0.000 | -2.017 |
| $C_{13}$ | -2.163 | -1.396 | -2.918 | 0.141 | 0.129 | -2.020 | 0.091 | -1.974 | -2.741 | 0.191 | 0.132 | 0.179 |
| $C_{14}$ | -3.134 | -2.823 | -3.597 | 0.177 | 0.085 | -1.957 | 0.160 | -1.499 | -2.278 | 0.204 | 0.111 | 0.129 |
| $C_{15}$ | -1.742 | -2.522 | -2.913 | 0.132 | -1.954 | -2.436 | 0.190 | 0.148 | -1.530 | 0.220 | 0.184 | 0.116 |

Table 4.24: Final matrices of dominance

| Dominance between [,] | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
|---|---|---|---|---|
| $S_1$ | 0.000 | -18.225 | -36.043 | -41.419 |
| $S_2$ | -8.465 | 0.000 | -29.372 | -36.999 |
| $S_3$ | 2.396 | -1.472 | 0.000 | -18.176 |
| $S_4$ | 2.717 | 2.447 | -4.413 | 0.000 |

Table 4.25: Global measure of dominance of each alternative, corresponding global index measure and final ranking order

| Alternatives | $\sum_{j=1}^{n}\delta(A_i, A_j)$ | $\xi_i$ | Ranking order (by Fuzzy-TODIM) |
|---|---|---|---|
| $S_1$ | -95.687 | 0.00 | 4 |
| $S_2$ | -74.836 | 0.22 | 3 |
| $S_3$ | -17.252 | 0.81 | 2 |
| $S_4$ | 0.7510 | 1.00 | 1 |

# Chapter 5

# A Novel Decision Support Framework for Selection of 3PL Service Providers: A Dominance-Based Approach in Combination with Grey Set Theory

## 5.1 Coverage

Since past two decades, logistics outsourcing has got immense importance in the context of supply chain management. Logistics outsourcing or outsourcing of third party logistics (3PL) comprises involvement of outside firms to execute logistics activities of a firm efficiently. As deployment of 3PL service providers has gained huge momentum in recent times, appropriate selection of 3PL service providers seems indeed a necessity. The present work intends to propose a decision support framework for evaluation and selection of 3PL service providers in pursuit of fulfilling various business needs. A decision support framework based on dominance measure concept integrated with grey set theory has been projected herein. Result obtained thereof, has been compared to that of grey-TOPSIS. A case empirical research has also been reported.

The proposed dominance based decision support system in light of grey set theory has been conceptualized is basically a simplified version of TODIM and PROMETHEE. It explores dominance between two alternatives with respect to a particular criterion; based on which a global dominance measure is computed to derive ranking order of candidate 3PL providers. The proposed approach delineated in this research seems straightforward, easy to execute and can exclude complex and tedious computational steps of TODIM as well as PROMETHEE.

## 5.2 Background and Problem Statement

Supply chain management is the key managerial concept for the organizations involved in production and distribution of the goods to deal with the flow of product, information, and finance. The product flow consists movement of raw or finished products from company to consumer (forward path); from consumer to company (backward path) in case of reverse supply chain management. The information flow takes care of necessary information about the status of order and delivery; while financial flow involves all about the payment and credit terms. The responsiveness and efficiency of supply chain management mostly depend on the supply chain drivers. Although there exists a number of supply chain drivers like inventory, transportation, facilities, information, sourcing and pricing; out of them logistics (transport, courier, distribution, etc.) appear as the backbone of the business. Without logistic services, goods cannot be transported to the manufacturer from the supplier and ultimately to the consumer, in a timely and cost-effective manner. Industries have now realized that it is not possible to establish and maintain an inclusive system responsible for the movement of raw materials and finished products along with their routine production work, simultaneously. Afterward, it has been agreed commonly that to achieve various organizational goals well in time, association of external 3PL service providers is a vital requirement.

The assigned 3PL partner is fully accountable to execute all the services related to transportation/delivery of goods before and after production. In order to ensure business excellence in the competitive global market, companies have realized that they must work together in a synchronized way with their logistics associates. Outsourcing of 3PL, is defined as a provision of exploring single or multiple logistics services by a vendor on a contractual basis (Razzaque and Sheng, 1998). 3PL providers are supposed to perform a variety of logistics functions, such as inbound transport, outbound transport, warehousing and reverse logistics activities. Therefore, outsourcing of logistics to 3PL providers has become an increasingly powerful trend in modern companies (Qureshi et al., 2008a). Third party logistics providers are basically from autonomous organizations offering single/multi-logistic facilities to a manufacturing unit. 3PL providers do not possess the ownership of the product retained for the distribution purpose but legally bound to execute the requested logistic activities. The request may also be logged to the reverse pick up of previously delivered (already consumed by the customers) products and this kind of service is widely known in supply chain literature as reverse logistic services. Companies are looking forward to provide a hassle free service to their customers and to ensure quick response to the same. Not only in forward supply chain management, outsourcing of logistics services is also needed in reverse supply chain management deploying third party reverse logistics (3PRL) service providers.

Reverse logistics is primarily associated with the management of returned products (Luttwak, 1971; Kannan, 2009). Reverse logistics primarily deals with procedure of reprocessing products. From retailers' viewpoint, reverse logistics is a way to get a product returned by the consumer back to the vendor (Buxbaum, 1998). Reverse logistics literature generally refers to the collected products as commercial returns and end-of-life returns. Reverse logistics involves the process of planning, implementing, and controlling the efficient, cost-effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal (Rogers and Tibben-Lembke, 1999; Kannan, 2009). According to (Schwartz, 2000), reverse logistics plays an important role for a company to gain competitive advantage.

To summarize, it has been found from the literature survey that outsourcing has got huge response providing long-term potential for the companies to survive; consequently, 3PL provider firms have an excellent opportunity to enter in this market. Apart from 3PL; deployment of 3PRL providers are seemed indeed a necessity since many corporations are unable to handle the complex networking necessary to have a well-organized reverse logistics process (Cottrill, 2000; Meyer, 1999; Rosen, 2001; Song et al., 2000). As a result, an emerging demand for 3PL/3PRL services is felt across the globe depending upon the levels of complexity and the precision (Maloni and Carter, 2006). Selection of an appropriate 3PL/3PRL service partner is very important to satisfy stringent business needs. According to (Büyüközkan et al., 2008), the selection of a suitable 3PL partner for a strategic alliance is a decision making task associated with uncertainty and complexity.

To this end, the present work conceptualizes a novel decision support framework towards evaluation and selection of 3PL providers under 'grey' (uncertain) environment. Grey numbers set theory has been delineated herein to overcome inconsistency, incompleteness and imprecision of subjective human judgment against vague (ill-defined) criteria-attributes. A dominance based approach in 'grey' environment has been proposed which is basically a simplified version of TODIM (an acronym in Portuguese of Interactive and Multi-Criteria Decision Making "*Tomada de Decisão Iterativa Multicritério*") as well as PROMETHEE (*Preference Ranking Organization Method for Enrichment Evaluation*). The proposed decision support system seems quite straightforward and it avoids complex computational steps of TODIM as well as PROMETHEE.

Bottani and Rizzi (2006) presented a multi-attribute approach combining TOPSIS technique (*Technique for Order Preference by Similarity to Ideal Solution*) and the fuzzy set theory for the selection and ranking of the most suitable 3PL service provider. Kahraman et al. (2007) also developed a hierarchical fuzzy-TOPSIS for evaluating and selecting among logistic information technologies. Işıklar et al. (2007) proposed a framework for effective 3PL evaluation and selection by integrating case-based reasoning, rule-based reasoning and compromise programming techniques in fuzzy environment. Büyüközkan et al. (2008) proposed a Multi-Criteria Decision Making (MCDM) approach combining Analytic Hierarchy Process (AHP) and TOPSIS to effectively evaluate e-logistics-based strategic alliance partners. Efendigil et al. (2008) aimed to assist the decision makers in determining the 'most appropriate' 3PRL provider using a two-phase model based on artificial neural networks and fuzzy logic.

Qureshi et al. (2008a) developed an integrated model, in order to identify and classify, key criteria, and to study their role in the selection process of third party logistics services providers for shippers' logistics need. An integrated model using Interpretive Structural Modeling (ISM) and fuzzy MICMAC (*Matrice d'Impacts croises-multipication appliqué an classment*) analysis was developed to identify and classify the key selection criteria of 3PL services providers, typically identified by many researchers and practiced by the shippers for effective supply chain management. The key criteria were also modeled to find their role and mutual influence in the selection of 3PL services providers. Qureshi et al. (2008b) described TOPSIS for critically analyzing and selecting potential 3PL service providers in fuzzy environment. Various selection criteria measured in linguistics term in vague and subjective reference were accounted using Triangular Fuzzy Numbers (TIFNs).

The case problem demonstrated fuzzy MCDM method to evaluate the potential 3PL service providers by assigning weight to each criterion and later on synthesizing the capability exhibited by them. In another reporting, (Qureshi et al., 2009b) proposed a methodology based on digraph and matrix approach for evaluating alternative logistics services providers (LSPs). An LSP selection index that evaluated and ranked the LSPs was derived from an LSP selection attributes' function, obtained from the digraph of LSP selection attributes. The digraph was developed considering LSP selection attributes under fuzzy environment. Coefficients of similarity, coefficients of dissimilarity and the identification sets were further proposed for comparison of candidate LSPs.

Kannan et al. (2009) developed a fuzzy based Multi-Criteria Group Decision Making (MCGDM) model to guide the selection process of best 3PRL providers. The analysis was done through ISM and fuzzy-TOPSIS. Kannan (2009) proposed a structured model by adopting multi-criteria decision making tools such as AHP and fuzzy Analytic Hierarchy Process (FAHP) for evaluating and selecting the best 3PRL provider under fuzzy environment for the battery industry, India. Perçin (2009) provided a good insight into the use of a-two-phase analytical hierarchy process and TOPSIS in the evaluation of 3PL providers. After the selection criteria of 3PL providers were determined by modified Delphi method, the weights of criteria were calculated by applying the AHP method. The TOPSIS method was then employed to achieve the final ranking results. Sensitivity analysis was also performed to demonstrate sensitivity of the proposed model to changes in the weights of different main criteria.

Liu and Wang (2009) presented an integrated fuzzy approach for the evaluation and selection of 3PL providers. This method consisted of three different techniques: (1) use fuzzy Delphi method to identify important evaluation criteria; (2) apply fuzzy inference method to eliminate unsuitable 3PL providers; and, (3) develop a fuzzy linear assignment approach for the final selection. Chen et al. (2010) combined the linguistic PROMETHEE method with maximum deviation method to determine the ranking order of logistics suppliers. Vijayvargiya and Dey (2010) provided a structured decision making model for selection of the most suitable logistics provider using AHP. With this technique, several criteria like freight charges, inland charges, schedule flexibility, warehousing capacity, track and trace system, port presence and custom clearance were considered to select a suitable logistics provider. Bhatti et al. (2010) carried out AHP modeling for selection of third party logistics service providers in global lead logistics provider (LLP) environments with necessary inputs from the Indian LLPs and the Indian service providers. Azadi and Saen (2011) proposed a Chance-Constrained Data Envelopment Analysis (CCDEA) approach to assist the decision makers to determine the most appropriate third party reverse logistics providers in the presence of both dual-role factors and stochastic data. Govindan and Murugesan (2011) proposed a structured model of fuzzy extent analysis for the selection of a 3PRL provider under fuzzy environment for the battery industry, which established relative weights for attributes and sub-attributes. Banomyong and Supatn (2011b) identified key attributes of freight logistics service quality and examined how these attributes could impact shippers' selection of 3PL providers. Logistics regression analyses were performed to examine the impact of freight logistics service attributes on shippers' decision to select 3PLs. Various freight logistics service attributes were identified and categorized based on the SERVQUAL model into six dimensions: reliability, assurance, tangibility, empathy, responsiveness, and cost.

Govindan et al. (2012) adopted Interpretive Structural Modeling (ISM) methodology for identifying and summarizing relationships among specific attributes for selecting the best third party reverse logistics provider. Ho et al. (2012) developed an integrated approach, combining Quality Function Deployment (QFD), fuzzy set theory, and analytic hierarchy process, to evaluate and select the optimal third party logistics service providers. In the approach, multiple evaluating criteria were derived from the requirements of company stakeholders using a series of House Of Quality (HOQ). The importance of evaluating criteria was prioritized with respect to the degree of achieving the stakeholder requirements using fuzzy-AHP. Based on the ranked criteria, alternative 3PLs were evaluated and compared with each other using fuzzy-AHP again to make an optimal selection. The effectiveness of proposed approach was demonstrated by applying it to a Hong Kong based enterprise dealing with hard disk components. Falsini et al. (2012) proposed a mathematical method that combined AHP, DEA and linear programming in order to support multi-criteria evaluation of third party logistics service providers. The proposed model aimed to improve the AHP method, merging experts' indications with objective judgments originating from historical data analysis. Suppliers' past performance was thus used to correct eventual errors resulting from the acceptance of interviews where the consistency ratio was high. Daim et al. (2012) presented analytic hierarchy process and hierarchical decision model approaches for selecting a 3PL service provider. Kumar and Singh (2012) proposed an integrated approach of fuzzy-AHP and TOPSIS in evaluating the performance of global third party logistics service providers for effective supply chain management. The integration of fuzzy AHP with TOPSIS was proposed in determining the relative importance (weight) of criteria and then ranking of 3PL providers. Findings showed that the logistics cost and service quality were the two most important criteria for performance rating of 3PL providers. Perçin and Min (2013) proposed a hybrid QFD and fuzzy decision making methodology for solving 3PL evaluation/selection problem. First, QFD was utilized to structure specific customer service needs and to match those needs to the characteristics of 3PL candidates. Fuzzy linear regression modeling was then employed to determine a functional relationship between the 3PL user's logistics service needs and the 3PL characteristics. Finally, a zero-one goal programming model was used to select the most desirable 3PL under multiple decision criteria.

Senthil et al. (2014) proposed a hybrid method using AHP and fuzzy-TOPSIS for contractor evaluation and selection in third-party reverse logistics. AHP was used to obtain the initial weights and fuzzy-TOPSIS was used to get the final ranking. Finally, a sensitivity analysis was carried out to confirm the robustness. Sahu et al. (2015b) proposed a fuzzy based appraisement platform for evaluation and selection of 3PL providers. The theory of Interval-Valued Fuzzy Numbers (IVFNs) was utilized to aid the proposed decision modeling. The contributions were: First, development and implementation of a decision making procedural hierarchy to support 3PL evaluation and selection; secondly, determination of an overall performance metric; thirdly, to explore the concept of IVFNs set theory to facilitate such a decision making. Finally, the appraisement index system was extended with the capability to search ill-performing areas of individual 3PL providers requiring future progress.

A variety of decision support systems have been well articulated in past literature in the domain of Multi-Criteria Decision Making (MCDM) [Kou et al., 2013; Kou et al., 2014a; Kou and Lin, 2014], with adequate emphasis on 3PL service provider selection. Since majority of the evaluation criteria being subjective, decision information possess multi-possibility and ambiguity. Hence, application of fuzzy set theory has been attempted by pioneers to tackle those ill-defined and vague evaluation criteria. Exploration of grey numbers set theory seems helpful in this context; since, grey numbers also possess the capability to take care of uncertainties involved in subjective decision judgment provided by a group of Decision-Makers. In this context, the present work proposes a novel decision support framework: dominance based approach in combination with grey numbers set theory to facilitate 3PL service provider selection. The 3PL alternative selection has been performed in view of the following criteria: Third party logistics services; Reverse logistics functions; Organizational role; User satisfaction; Impact of use of 3PL; Organizational performance; IT application. Uncertainties involved in subjective human (Decision-Maker) judgment on assessing 3PL performance indices have been tackled by grey numbers set theory. The proposed decision making approach seems straightforward; exhibits few similarities to TODIM and PROMETHEE. But it avoids complex computational parts of TODIM as well as PROMETHEE. The result of the proposed decision support framework has been compared to that of grey-TOPSIS.

## 5.3 Research Methodology

'Grey' means somewhat hazy (fuzzy) i.e. incomplete or uncertain (inexact). The grey number can be defined as the number with a general range, but the exact value of this number cannot be known (Wang et al., 2013). In application, the grey number is an uncertain number which takes the value in a scope or a particular number set. The preliminaries of grey numbers set theory have already been provided in **Section 3.1.2.3.1**.

## 5.4 Proposed Decision Support Framework

In this work, dominance based decision support system in light of grey numbers set theory has been conceptualized by adapting preliminary formulations of dominance measure from TODIM as well as PROMETHEE.

The TODIM method makes use of the prospect function to calculate the dominance of one alternative over another. According to (Kahneman and Tversky, 1979), human thought is not completely rational presenting strong bias in some situations. For instance, people are more sensitive to losses than they are to gains. In order to consider the human bias in the MCDM methods, (Gomes and Lima, 1992) proposed the TODIM method, one of the first MCDM methods grounded on the Prospect Theory. This method was found fruitful when applied to many MCDM problems e.g., (Gomes and Rangel, 2009; Gomes et al., 2009). Also, TODIM method was extended to deal with fuzzy numbers (Krohling and de Souza, 2012). Whereas, PROMETHEE method is made first to calculate the dominance degree matrices for each criterion matrices for each criterion; second, to aggregate these matrices into the overall dominance matrix; third, to compute the outgoing flow, entering flow and net flow; finally, to obtain the final ranking order based on the obtained net flows. Here, first the deviation is computed based on pairwise comparisons (the difference of the ratings) and then it is applied to a preference function (Behzadian et al., 2010). Therefore, in PROMETHEE, prospect function (from TODIM) is replaced by preference function. But, in the proposed decision support system, the tedious computations in relation to prospect value function (as in case of TODIM) or preference function (as in case of PROMETHEE) can be excluded.

The proposed approach only explores dominance between two alternatives with respect to a particular criterion; based on which a global dominance measure is computed to facilitate ranking order determination of alternative candidate suppliers. The proposed approach delineated in this research seems straightforward which can exclude complex computational steps of TODIM as well as PROMETHEE. Moreover, TODIM literature depicts that the formulations are based on computing crisp weight (and also relative weight) of criteria. It is very difficult to obtain exact (precise) criteria weight; since, in reality most of the criteria are subjective type and evaluation of which possesses ambiguity and multi-possibility. In TODIM, while computing prospect value function (in relation to gain/loss); the attenuation factor $\theta$ has to be set.

The parameter $\theta$ in TODIM controls the impact incurred in case of losses. If $\theta < 1$, the losses are amplified; and if $\theta > 1$, the losses are attenuated. The prospect theory states that the individuals are more sensitive to losses than to gains, suggesting $\theta < 1$. However, in most of the cases TODIM assumes, $\theta \geq 1$. According to (Lourenzutti and Krohling, 2014), this parameter can considerably affect the ranking order of the alternative. Therefore, the section of $\theta$ is also the discretion of the Decision-Maker. This may create variation in the final decision outcome. Hence, in this work, an attempt has been made to develop a dominance based decision making approach in integration with grey numbers set theory towards rational decision making. This seems to be a simple and straightforward approach as compared to TODIM as well as PROMETHEE. Application potential of the proposed approach has also been compared to that of grey-TOPSIS.

The procedural steps of the proposed decision support framework have been summarized as follows:

1. Realization of the decision making problem consisting a set of alternatives and a set of decision criteria; formation of a decision making group.
2. Selection of linguistic scales towards assigning criteria weight as well as appropriateness rating of alternatives with respect to individual criterion; also collection of decision making data.
3. Transformation of linguistic data into appropriate grey numbers representation; aggregation of decision-makers' pulled opinion.
4. Establishing grey multi-attribute decision making matrix.
5. Normalizing grey decision matrix.
6. Construction of grey weighted normalized decision matrix.
7. Computation of partial matrices of dominance.
8. Computation of final matrices of dominance.
9. Computation of global measure and final ranking order of alternatives.

**Step 1:** Assume that $S = \{S_1, S_2, ..., S_m\}$ is a discrete set of $m$ possible alternatives; also, assume $C = \{C_1, C_2, ..., C_n\}$ is a set of $n$ evaluation criteria/attributes. The attributes are additively independent (i.e. uncorrelated to each other). Form a committee of decision-makers (DMs) towards assigning criteria weights as well as ratings of alternatives with respect to various attributes/criteria.

**Step 2:** Select appropriate linguistic term sets to be utilized by the DMs for appraising various alternatives with respect to different attributes as well as for assignment of criteria weights. Also, collect decision making data i.e. linguistic judgment of the experts.

**Step 3:** Linguistic expert judgment is to be transformed into appropriate grey numbers. Individual DMs preferences (grey ratings) are to be aggregated by using the following formulation (Eq. 5.1). Assume that a decision making group consists of $k$ persons; then the aggregated rating $\otimes G_{ij}$ can be computed as:

$$\otimes G_{ij} = \frac{1}{K}[\otimes G_{ij}^{1} + \otimes G_{ij}^{2} + ... + \otimes G_{ij}^{K}] \quad (5.1)$$

where, $\otimes G_{ij}^{k} \quad (i = 1,2,..., m; j = 1,2,..., n)$ is the attribute rating given by $k^{th}$ DM which can be described by the grey number $\otimes G_{ij}^{k} = [\underline{G}_{ij}^{k}, \overline{G}_{ij}^{k}]$.

Similarly, $\otimes w_j = \frac{1}{K}\left[\otimes w_j^{1} + \otimes w_j^{2} + ... + \otimes w_j^{K}\right]$ (5.2)

where, $\otimes w_j^{k} \quad (i = 1,2,..., m; j = 1,2,..., n)$ is the weight of $j^{th}$ criteria given by $k^{th}$ DM which can be described by the grey number $\otimes w_j^{k} = [\underline{w}_j^{k}, \overline{w}_j^{k}]$.

**Step 4:** Establish the grey multi-attribute decision-making matrix.

$$\mathbf{D} = \begin{bmatrix} \otimes G_{11} & \otimes G_{12} & \cdots & \otimes G_{1n} \\ \otimes G_{21} & \otimes G_{22} & \cdots & \otimes G_{2n} \\ \vdots & & \ddots & \vdots \\ \otimes G_{m1} & \otimes G_{m2} & \cdots & \otimes G_{mn} \end{bmatrix} \quad (5.3)$$

where $\otimes G_{ij}$ is the aggregated grey rating of $i^{th}$ alternative with respect to $j^{th}$ criterion.

**Step 5:** Normalize the grey decision matrix:

$$\mathbf{D}^{*} = \begin{bmatrix} \otimes G_{11}^{*} & \otimes G_{12}^{*} & \cdots & \otimes G_{1n}^{*} \\ \otimes G_{21}^{*} & \otimes G_{22}^{*} & \cdots & \otimes G_{2n}^{*} \\ \vdots & & \ddots & \vdots \\ \otimes G_{m1}^{*} & \otimes G_{m2}^{*} & \cdots & \otimes G_{mn}^{*} \end{bmatrix} \quad (5.4)$$

For a benefit attribute, $\otimes G_{ij}^{*}$ is expressed as:

$$\otimes G_{ij}^{*} = \left[\frac{\underline{G}_{ij}}{G_j^{\max}}, \frac{\overline{G}_{ij}}{G_j^{\max}}\right]. \quad (5.5)$$

Here, $G_j^{\max} = \max_{1 \le i \le m}\{\overline{G}_{ij}\}$ (5.6)

For a cost attribute, $\otimes G_{ij}^{*}$ is expressed as:

$$\otimes G_{ij}^{*} = \left[ \frac{G_{j}^{\min}}{\overline{G}_{ij}}, \frac{G_{j}^{\min}}{\underline{G}_{ij}} \right] \tag{5.7}$$

Here, $G_{j}^{\min} = \min_{1 \le i \le m} \{\underline{G}_{ij}\}$ (5.8)

The normalization method mentioned above is to preserve the property that the ranges of the normalized grey number belong to $[0,1]$.

**Step 6:** Construct grey weighted normalized decision matrix.

$$\mathbf{V} = \begin{bmatrix} \otimes v_{11} & \otimes v_{12} & \cdots & \otimes v_{1n} \\ \otimes v_{21} & \otimes v_{22} & \cdots & \otimes v_{2n} \\ \vdots & & \ddots & \vdots \\ \otimes v_{m1} & \otimes v_{m2} & \cdots & \otimes v_{mn} \end{bmatrix} \tag{5.9}$$

where $\otimes v_{ij} = \otimes G_{ij}^{*} \times \otimes w_{j}$ (5.10)

**Step 7:** Computation of partial matrices of dominance.

After constructing grey weighted normalized decision matrix, the partial dominance matrices and the final matrices of dominance are to be computed next.

Calculate the partial matrices of dominance $\phi_c(A_p, A_q)$ using Eq. (5.11). The term $\phi_c(A_p, A_q)$ represents the contribution of the criterion $c$ to the function $\delta(A_p, A_q)$ i.e. global dominance when comparing alternative $p$ with alternative $q$.

$$\phi_c(A_p, A_q) = \begin{cases} d(\otimes v_{pc}, \otimes v_{qc}), & if\ [\otimes v_{pc} > \otimes v_{qc}] \\ 0, & if\ [\otimes v_{pc} = \otimes v_{qc}] \\ -d(\otimes v_{pc}, \otimes v_{qc}), & if\ [\otimes v_{pc} < \otimes v_{qc}] \end{cases} \tag{5.11}$$

In this expression, $\otimes v_{pc}$ and $\otimes v_{qc}$ stand for the weighted normalized grey rating against criterion $c$ for two alternatives $A_p$ and $A_q$, respectively. Now, while comparing $\otimes v_{pc}$ and

$\otimes v_{qc}$ the concept of grey possibility degree needs to be explored here (**Section 3.1.2.3.1**; **Definition 10**).

The term $d(\otimes v_{pc}, \otimes v_{qc})$ designates the distance between the two grey numbers $\otimes v_{pc}$ and $\otimes v_{qc}$, as defined in Eq. (3.35) (**Section 3.1.2.3.1**; **Definition 9**).

Three cases can occur in Eq. (5.11):

a) if the value $\lfloor \otimes v_{pc} > \otimes v_{qc} \rfloor$, it represents dominance (alternative $p$ is dominating alternative $q$);

b) (ii) if the value $\lfloor \otimes v_{pc} = \otimes v_{qc} \rfloor$, there is nil dominance (i.e. $p$ is not dominating $q$, and vice versa)

c) (iii) if the value $\lfloor \otimes v_{pc} < \otimes v_{qc} \rfloor$, it represents a negative dominance i.e. alternative $q$ is dominating alternative $p$ or (alternative $p$ is dominated by alternative $q$).

In (Eq. 5.11), the distance measure between two grey numbers i.e. $d(\otimes v_{pc}, \otimes v_{qc})$ being a crisp value (exact value/ precise information); appropriate sign has to be considered separately to indicate whether alternative $p$ is dominating alternative $q$ (positive dominance); or alternative $p$ is dominated by alternative $q$ (negative dominance).

**Step 8:** The final matrix of dominance is obtained by summing up the partial matrices of dominance of each criterion.

$$\delta(A_p, A_q) = \sum_{c=1}^{n} \phi_c(A_p, A_q) \quad \forall (p,q) \tag{5.12}$$

**Step 9:** Calculate the global value of the alternative $\xi$ by normalizing the final matrix of dominance according to the following expression.

$$\xi = \frac{\sum \delta(p,q) - \min \sum \delta(p,q)}{\max \sum \delta(p,q) - \min \sum \delta(p,q)} \tag{5.13}$$

Ordering the values $\xi$ provides the rank of each alternative. The best alternative is one that has the highest value of $\xi$.

## 5.5 Basics of Grey-TOPSIS

Technique for order preference by similarity to ideal solution (TOPSIS) was developed by (Hwang and Yoon, 1981) to rank alternatives over multiple criteria. TOPSIS finds the best alternative by minimizing the distance to the ideal solution or positive ideal solution and maximizing the distance to the negative ideal solution or anti-ideal solution. The preliminaries of TOPSIS considering crisp evaluation data could be well articulated from (Kou et al., 2014b). However, the situation when decision making has to be carried out based on linguistic preferences of the Decision-Makers' (DMs') due to involvement of subjective evaluation criteria; traditional TOPSIS integrated with grey set theory may be fruitful.

The procedural steps of grey-TOPSIS have been summarized as follows:

1. Realization of the decision making problem.
2. Collection of decision making data.
3. Establishing grey multi-attribute decision making matrix.
4. Normalizing grey decision matrix.
5. Computation of weighted normalized decision matrix.
6. Computation of distance measures of each of the alternatives with respect to both positive-ideal solution and negative-ideal solution.
7. Computation of closeness coefficient for individual alternatives.
8. Determination of ranking order.

In grey-TOPSIS, starting from the weighted normalized decision making matrix (refer to Eqs. 5.9-5.10), the positive and negative ideal alternatives are to be determined. The positive ideal alternative $A^{+}$, and the negative ideal alternative $A^{-}$, can be defined as:

$$A^{+} = \left\{ \left[ \max_{1\le i\le m} \underline{v}_{i1}, \max_{1\le i\le m} \bar{v}_{i1} \right], \left[ \max_{1\le i\le m} \underline{v}_{i2}, \max_{1\le i\le m} \bar{v}_{i2} \right], \ldots, \left[ \max_{1\le i\le m} \underline{v}_{in}, \max_{1\le i\le m} \bar{v}_{in} \right] \right\}$$

$$= \left\{ \otimes v_1^{+}, \otimes v_2^{+}, \ldots, \otimes v_n^{+} \right\}$$

$$= \left\{ \left( \underline{v}_1^{+}, \bar{v}_1^{+} \right), \left( \underline{v}_2^{+}, \bar{v}_2^{+} \right), \ldots, \left( \underline{v}_n^{+}, \bar{v}_n^{+} \right) \right\} \tag{5.14}$$

$$A^{-} = \left\{ \left[ \min_{1 \le i \le m} \underline{v}_{i1}, \min_{1 \le i \le m} \bar{v}_{i1} \right], \left[ \min_{1 \le i \le m} \underline{v}_{i2}, \min_{1 \le i \le m} \bar{v}_{i2} \right], \ldots, \left[ \min_{1 \le i \le m} \underline{v}_{in}, \min_{1 \le i \le m} \bar{v}_{in} \right] \right\}$$

$$= \left\{ \otimes v_1^{-}, \otimes v_2^{-}, \ldots, \otimes v_n^{-} \right\}$$

$$= \left\{ \left( \underline{v}_1^{-}, \bar{v}_1^{-} \right), \left( \underline{v}_2^{-}, \bar{v}_2^{-} \right), \ldots, \left( \underline{v}_n^{-}, \bar{v}_n^{-} \right) \right\} \tag{5.15}$$

Next, distances of each alternative with respect to the positive ideal solution and the negative ideal solution ($d_i^{+}$ and $d_i^{-}$, respectively) are computed.

$$d_i^{+} = \sum_{j=1}^{n} \sqrt{\frac{1}{2}\left[ \left( \underline{v}_j^{+} - \underline{v}_{ij} \right)^2 + \left( \bar{v}_j^{+} - \bar{v}_{ij} \right)^2 \right]} \tag{5.16}$$

$$d_i^{-} = \sum_{j=1}^{n} \sqrt{\frac{1}{2}\left[ \left( \underline{v}_j^{-} - \underline{v}_{ij} \right)^2 + \left( \bar{v}_j^{-} - \bar{v}_{ij} \right)^2 \right]} \tag{5.17}$$

The relative closeness, $C_i^{+}$ with respect to the positive ideal solution is computed by using Eq. (5.18).

$$C_i^{+} = \frac{d_i^{-}}{d_i^{+} + d_i^{-}} \tag{5.18}$$

Here, $0 \le C_i^{+} \le 1$. The larger index value is the better evaluation of the alternative. The set of alternatives now can be preferentially ranked by the descending order of the value of $C_i^{+}$

## 5.6 Case Illustration

An empirical case illustration has been demonstrated herein in pursuit of evaluation and selection of appropriate 3PL service provider alternative using the proposed dominance based decision making approach in combination with grey numbers set theory. A list of relevant criteria for 3PL provider selection has been shown in Table 5.1. A total of thirty five criteria have been considered from seven broad performance dimensions viz. third party logistics services, reverse logistics functions, organizational role, user satisfaction, impact of use of 3PL, organizational performance criteria, and IT application. The definitions of aforesaid criteria have also been furnished in Table 5.1. Since all evaluation criteria seem ill-defined (vague); these are to be evaluated in a subjective way rather than objective. A decision making group needs to take part to assess these criteria by using linguistic variables. Two sets of linguistic variables have been explored to assign priority weight of criteria and the suitability of alternative 3PL providers with respect to the criteria, respectively.

A committee of five Decision-Makers (DMs) (DM1, DM2, DM3, DM4, DM5) has been constructed in order to evaluate the best 3PL provider amongst a set of four candidate 3PL provider alternatives viz. 3PL1 ($A_1$), 3PL2 ($A_2$), 3PL3 ($A_3$), and 3PL4 ($A_4$). The following linguistic terms set: (Refer to Table 5.2) has been utilized to assign criteria weights. Similarly, the linguistic terms set (shown in Table 5.2) has been explored to rate alternative 3PL providers with respect to the evaluation criteria ($C_1$ to $C_{35}$). DMs have been instructed to use these linguistic terminologies towards assigning criteria weight and appropriateness (rating) of alternatives with respect to criteria. The weights of criteria expressed by linguistic variables as given by the DMs have been depicted in Table 5.3. Linguistic ratings of 3PL alternatives with respect to criteria as given by the DMs have been provided in Table 5.4. Since subjective human judgment bears some sort of ambiguity and vagueness; aforesaid linguistic data have been transformed into appropriate grey numbers in accordance with Table 5.2.

Next, DMs judgments have been pulled to compute aggregated grey rating of alternatives with respect to criteria (using Eq. 5.1); results have been shown in Table 5.5 (initial decision matrix). Similarly, aggregated grey weights of criteria have been determined (using Eq. 5.7) and shown in Table 5.5. Aggregated grey ratings of alternatives (with respect to criteria) have been normalized (using Eq. 5.5; assuming all criteria are beneficial) to construct the grey normalized decision matrix (as shown in Table 5.6). For individual alternatives, normalized ratings of criteria have been multiplied (using Eq. 5.10) with aggregated grey criteria weight to construct the grey weighted normalized decision matrix (as shown in Table 5.7). Now, partial matrices of dominance has been constructed by exploring (Eq. 5.11) and shown in Table 5.8.

In constructing partial matrices of dominance, the weighted normalized grey ratings (with respect to a particular criterion) for a pair of alternatives have been compared. If the weighted normalized grey rating of first alternative is greater than that of the second; it is inferred that the first alternative is dominating the second and the other way around. In order to compare weighted normalized grey ratings of two alternatives, the concept of grey possibility degree (Refer to: **Section 3.1.2.3.1; Definition 10**) has been explored. In computation of dominance measure, Eq. (3.35) **(Section 3.1.2.3.1; Definition 9)** i.e. the formula for computing distance between two grey numbers has been utilized. In conceptualizing degree of dominance, proper sign consideration has been taken care of to indicate whether one alternative is dominating the other (dominance measure is positive) or vice versa (i.e. negative dominance measure). The final matrix of dominance has been constructed next (by using Eq. 5.12) and placed in Table 5.9. Finally, the global value $\xi$ of each alternative has been determined by normalizing the final matrix of dominance (according to Eq. 5.13) as shown in Table 5.10. The ranking order of alternative 3PL providers appears as $A_4 > A_2 > A_1 > A_3$. The fourth alternative 3PL4 ($A_4$) is the best choice amongst the candidate set; whereas, the third alternative 3PL3 ($A_3$) is considered as the worst (Table 5.10).

## 5.7 Discussion: Comparison with Grey-TOPSIS

By applying Grey-TOPSIS (Refer to: **Section 5.5**), alternative 3PL providers have been ranked accordingly based on their closeness coefficient value (Table 5.11). Ranking order of alternative 3PL providers appears as: $A_4 > A_1 > A_2 > A_3$. Whereas, in case of the proposed dominance based approach, the ranking order appeared as: $A_4 > A_2 > A_1 > A_3$. It has been found that for both the cases, the most appropriate choice and the worst choice appear the same. This definitely proves consistency of the proposed dominance based approach in comparison with Grey-TOPSIS, the well-known decision making approach in grey theory. Apart from the best and the worst choice, for this particular case example, it has been found that ranking position alters for other alternatives. This may be due to the difference in the concept in analyzing decision making data. The proposed approach explores dominance between alternative pairs; whereas, Grey-TOPSIS explores distance measures for each alternatives with respect to both positive ideal solution and negative ideal solution.

## 5.8 Concluding Remarks

The credential that goes to 3PL service providers is due to the capability to tackle with the complexity in logistics associated with supply chain activities. By assigning a 3PL service provider to pursue various logistic activities in an effective way, organizations should undoubtedly focus on their primary business operations. Deployment of efficient 3PL providers seems to be fruitful in ensuring cost effective delivery to the customers along with enhanced speed and higher customer satisfaction rate. The selection of the most favorable 3PL is indeed a tough job. 3PL service provider selection is a kind of Multi-Criteria Decision Making (MCDM) issue possessing uncertainty in input information or vague representation of the data availed from the decision-makers.

Grey set theory has enough potential to deal with such kind of human knowledge representation which is basically vague and ambiguous in nature. The present research demonstrates a decision support framework based on dominance theory in integration with grey set theory to assist firm's management in defining an appropriate 3PL provider from amongst possible alternatives. Grey-TOPSIS approach has also been attempted to verify application potential of the proposed dominance based approach in grey context.

Results indicate that the best and the worst choice from amongst 3PL candidate alternatives remain the same. The decision support framework proposed herein may provide a strong basis to the supply chain managers for effective 3PL provider selection. This module may also help in identifying ill-performing (deficient) area(s) of individual 3PL alternative. However, it must be noted that the decision making data explored herein are truly empirical in nature; i.e. not collected from a particular case company. In practice, the top managerial body of the company should form the particular decision making group, consisting a finite number of decision-makers (DMs)/ experts. Experts may be from the members associated with company management, management consultants hired from outside, and/or even personnel from academia who possess expertise and vast experience to take part such industrial decision making tasks. Apart from conducting a real case study, empirical illustration has been provided in this work just to make readers understand about the application procedural steps of the proposed decision support system. In future, the proposed decision support framework may be implemented in real case studies.

Table 5.1: Criteria for 3PL service provider selection

| Performance dimensions | Criteria, $C_j$ | Citations/ References | Definition |
|---|---|---|---|
| Third party logistics services | Inventory replenishment, $C_1$ | Gunasekaran et al., 2001; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | This refers to a process of filling the empty stock by placing orders. This is necessary to avoid stock out condition. User's optimal ordering quantity is hard to estimate, so a flexible reorder policy is required that will maximize the profit per unit time under the condition of permissible delay in payments. |
| | Warehouse management, $C_2$ | Van and Zijm, 1999; Dowlatshahi, 2000; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Warehouse management is an essential part of supply chain activities whose primary focus is to maintain storage and control the movement of materials according to the demand. This whole process includes shipping, receiving, picking and delivery within the warehouse. Basically, there are three types of warehouses management activities, distribution warehouses, production warehouses, contract warehouses. |
| | Shipment consolidation, $C_3$ | Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Smaller shipments should be collected and shipped together to avail better freight rates and security. The companies operate under just-in-time thinking of purchasing should opt tor frequent shipment of small quantities. |
| | Carrier selection, $C_4$ | Holguin-Veras, 2002; Bun and Ishizuka, 2006; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Selection of reliable carrier and transportation mode are two key parameter of this study and should be done at high level of priority with a careful scrutiny process. Transportation providers are responsible to move the goods fast at the best possible rate with minimal risk of damage, loss or theft. |
| | Direct transportation services, $C_5$ | Kleinsorge et al., 1991; Holguin-Veras, 2002; Bun and Ishizuka, 2006; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | In many countries, direct transportation facility is the most preferable service which refers to the straight shipment of goods and services from origin to destination without any transhipment. Logistic system management should measure the operation efficiency along with the service effectiveness. |

Table 5.1 (continued): Criteria for 3PL service provider selection

| Performance dimensions | Criteria, $C_j$ | Citations/ References | Definition |
|---|---|---|---|
| Reverse logistics functions | Collection, $C_6$ | Pohlen and Farris, 1992; Schwartz, 2000; Meade and Sarkis, 2002; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | This is a process of collecting the used/delivered products from the client/customer to serve the purpose of taking product back for either warranty or regulatory reasons. |
| | Packing, $C_7$ | Dowlatshahi, 2000; Meade and Sarkis, 2002; Cochran` and Ramanujam, 2006; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Total expenditure is possible to reduce by selecting the appropriate packaging method. Despite of the method of packaging at the origin, 3PL are responsible to perform some additional services at destination for the hassle free delivery. |
| | Storage, $C_8$ | Pohlen and Farris, 1992; Meade and Sarkis, 2002; Kaliampakos et al., 2002; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | This refers to the additional space provided for the storage of the returned products. A plan must be made for the proper utilization of the available storage space. |
| | Sorting, $C_9$ | Pohlen and Farris, 1992; Schwartz, 2000; Meade and Sarkis, 2002; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Sorting is a function of warehousing logistics system through which received products are sort out and placed at appropriate place. This process can be made better by using the latest sorting technology. Sorting systems can sort various products by code, weight, shape, size, color and quality. Sorting is very essential to decide the necessary course of action with each product. |
| | Transitional processing, $C_{10}$ | Dijck, 1990; Pohlen and Farris, 1992; Meade and Sarkis, 2002; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | This transitional process categories and separates the reusable or functioning parts of the products. Transitional processing is necessary for the disassembly of the materials obtained through a reverse logistics process. The materials will eventually be integrated into the manufacturing process if found useful. |
| | Delivery, $C_{11}$ | Stock, 1990; Pohlen and Farris, 1992; Meade and Sarkis, 2002; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | In this phase the product that has arrived through the reverse logistic program is finally handed over to the manufacturer or supplier for further processing. Delivery is commonly referred as the final stage of the transportation system and its performance is measured by the speed and reliability. |

Table 5.1 (continued): Criteria for 3PL service provider selection

| Performance dimensions | Criteria, $C_j$ | Citations/ References | Definition |
|---|---|---|---|
| Organizational role | Reclaim, $C_{12}$ | Meade and Sarkis, 2002; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Where the sole purpose is to reclaim the product for storage, reuse, or other activities that may not be taken care of by the reverse logistics provider. It can also be understood as a process to regain possession of any product. |
| | Recycle, $C_{13}$ | Dowlatshahi, 2000; Meade and Sarkis, 2002; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | It refers to a process of changing the physical and/ or chemical composition of the product so that it can be available for reuse, recycle and recovery of material. |
| | Remanufacture, $C_{14}$ | Dowlatshahi, 2000; Meade and Sarkis, 2002; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | An ability to reproduce a product around a reusable core. |
| | Reuse, $C_{15}$ | Demir and Orhan, 2003; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Making the products for reuse with providing additional production requirement. |
| | Disposal, $C_{16}$ | Schwartz, 2000; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | It refers to a process of managing the waste, scrap etc. to avoid environmental pollution. Most of the industrial wastes can be reused or recycled under this category. This is also known as a process of sending the goods to their desired target. |

Table 5.1 (continued): Criteria for 3PL service provider selection

| Performance dimensions | Criteria, $C_j$ | Citations/ References | Definition |
|---|---|---|---|
| User satisfaction | Effective communication, $C_{17}$ | Bensaou, 1997; Mohr and Spekman, 1994; Kannan 2009; Govindan et al., 2012 | It refers to a healthy and effective communication between the organizations. Organizational relationship is much more dependent on the type of communication gone between their respective officials. The level of communication in buyer–supplier relations is positively related to the scope of electronic data interchange use. |
| | Service improvement, $C_{18}$ | Monczka et al., 1993; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | This refers to a positive change in the type of organizational service. Organization may grant some extra compensation or incentives to encourage service providers. They incorporate sharing of accomplished cost funds, giving consideration for expanded volumes, future business and recognizing supplier improvements through service award. |
| | Cost saving, $C_{19}$ | Boyson et al. 1999, Andersson and Norrman 2002, , Kannan 2009, Govindan and Murugesan 2011, Govindan et al. 2012 | Working with no plan and no vision condition in transportation and logistics system may cause companies to overpay, late delivery or miss delivery target and loss of valuable goods; so to avoid these condition a strong decision making approach is required to save cost in all respect. A healthy financial practice of the provider confirms the continuity of service with regular modification in the equipment used for the logistic purpose. |
| | Overall working relations, $C_{20}$ | Boyson et al., 1999; Lynch, 2000; Langley et al., 2002; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | It really matters to have a decent working connection with employees at the service provider’s end; else it might lead to strike, lockouts, harm, and other such unwanted exercises, which may affect the organization's logistics operations adversely. |

Table 5.1 (continued): Criteria for 3PL service provider selection

| Performance dimensions | Criteria, $C_j$ | Citations/ References | Definition |
|---|---|---|---|
| Impact of use of 3PL | Customer satisfaction, $C_{21}$ | Boyson et al., 1999; Lynch, 2000; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | The ultimate goal of any organization, business and service is to have/retain maximum numbers of satisfied customers, and it is possible by providing the same as expected with full of support if needed from. Impact of use of 3PL can be well understood through customer satisfaction extent. |
| | Frequent updating, $C_{22}$ | Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | It refers to the modification or improvements in the existing service after a regular interval. Introductions of changes and modifications in process technologies, organizational and operational practices occur most frequently in high-technology plants. In fact, rapid and repeated innovation implementation is absolutely central to any high-technology manufacturing operations. |
| | Profitability, $C_{23}$ | Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Profit is the capacity of a business to procure a benefit and it can be measured after it pays all costs. Profit is needed to survive the business for the long term. The annual profits of the service provider must have to show an upward trend. |
| | Employee morale, $C_{24}$ | Razzaque and Sheng, 1998; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | The willingness of the provider to retain some of the user’s logistics employees, who would otherwise become unemployed after the outsourcing contract, wards off any chance of sabotage. It also improves the goodwill between the user and the provider. |

Table 5.1 (continued): Criteria for 3PL service provider selection

| Performance dimensions | Criteria, $C_j$ | Citations/ References | Definition |
| --- | --- | --- | --- |
| Organizational performance criteria | Quality, $C_{25}$ | Boyson et al.,1999; Andersson and Norrman, 2002; Lynch, 2000; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | A good management of service provider is not believe to provide only good service to the user but may also foster a long-term relationship between the user and the provider. |
| | Cost, $C_{26}$ | Boyson et al., 1999; Lynch, 2000; Langley et al., 2002; Stock et al., 1998; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al. 2012 | It refers to the total cost of logistics outsourcing, which should be minimized. |
| | Time, $C_{27}$ | Kleindorfer and Partovi, 1990; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Significant organizational performance criteria consist of traditional strategic organizational metrics such as time. |
| | Flexibility, $C_{28}$ | Stank and Daugherty, 1997; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Flexibility in operations and delivery may enable the user to give customized service to its customers, particularly in special or no routine requests. |
| | Customer satisfaction, $C_{29}$ | Kim et al. 2004, Kim et al. 2007, Kannan 2009, Govindan and Murugesan 2011, Govindan et al. 2012 | In order to survive in this competitive market, companies should continue to improve their service performance effectively. According to a recent study network performance is considered as important for increasing customer service performance. |
| | Service, $C_{30}$ | Kleindorfer and Partovi, 1990; Stank and Daugherty, 1997; Govindan et al., 2012 | This refers to the type of facility provided by the service provider to enhance the customer and employee satisfaction ratio. |

Table 5.1 (continued): Criteria for 3PL service provider selection

| Performance dimensions | Criteria, $C_j$ | Citations/ References | Definition |
|---|---|---|---|
| IT application | Warehouse management, $C_{31}$ | Van and Zijm, 1999; Dowlatshahi, 2000; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Warehousing concerns those material handling activities that take place within the warehouse, receiving and shipping areas in order management. Application of IT may enhance efficiency of warehouse management. |
| | Order management, $C_{32}$ | Li et al., 2006; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | The sensitive variation in the usage of general ordering policy at a specific time. |
| | Supply chain planning, $C_{33}$ | Scalle and Cotteleer, 1999; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Enterprise resource planning (ERP) is a system planning all aspects of a business including production planning, purchasing, manufacturing, and sales, distribution, accounting, and customer service. |
| | Shipment and tracking, $C_{34}$ | Holguin-Veras, 2002; Bun and Ishizuka, 2006; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | A shipment uses one or more modes of transportation, including parcel delivery, postal service, courier, private truck, for-hire truck, rail, water, pipeline, air, and other modes. Internet online tracking tools provide more shipment details in less time. |
| | Freight payment, $C_{35}$ | Cochran and Ramanujam, 2006; Kannan, 2009; Govindan and Murugesan, 2011; Govindan et al., 2012 | Freight payments are incurred per container basis. If the container is not fully utilized, it costs the same, so the cost per box goes up. |

Table 5.2: The scale of criteria weights $\otimes w$ and ratings $\otimes G$ of alternatives (Source: Li et al., 2007b)

| Linguistic terms for assigning criteria weights | $\otimes w$ (corresponding grey numbers representation) | Linguistic terms for assigning criteria ratings | $\otimes G$ (corresponding grey numbers representation) |
|---|---|---|---|
| Very Low, VL | [0.0, 0.1] | Very Poor, VP | [0, 1] |
| Low, L | [0.1, 0.3] | Poor, P | [1, 3] |
| Medium Low, ML | [0.3, 0.4] | Medium Poor, MP | [3, 4] |
| Medium/ Moderate, M | [0.4, 0.5] | Fair, F | [4, 5] |
| Medium High, MH | [0.5, 0.6] | Medium Good, MG | [5, 6] |
| High, H | [0.6, 0.9] | Good, G | [6, 9] |
| Very High, VH | [0.9, 1.0] | Very Good, VG | [9, 10] |

Table 5.3: Weights of criteria expressed by linguistic variables as given by the DMs

| Criteria | Linguistic weights as given by the DMs | | | | |
|---|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 | DM5 |
| $C_1$ | H | H | H | H | H |
| $C_2$ | H | VH | H | VH | H |
| $C_3$ | MH | MH | H | H | H |
| $C_4$ | H | H | MH | H | VH |
| $C_5$ | H | VH | VH | H | H |
| $C_6$ | H | H | VH | H | H |
| $C_7$ | MH | H | H | MH | H |
| $C_8$ | H | H | H | H | H |
| $C_9$ | VH | H | VH | H | H |
| $C_{10}$ | VH | VH | VH | H | H |
| $C_{11}$ | H | H | H | H | H |
| $C_{12}$ | H | H | H | H | H |
| $C_{13}$ | VH | H | H | VH | H |
| $C_{14}$ | H | H | H | H | H |

Table 5.3 (continued): Weights of criteria expressed by linguistic variables as given by the DMs

| Criteria | Linguistic weights as given by the DMs | | | | |
|---|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 | DM5 |
| $C_{15}$ | VH | MH | MH | H | H |
| $C_{16}$ | M | MH | MH | MH | H |
| $C_{17}$ | H | H | H | MH | MH |
| $C_{18}$ | H | H | H | H | H |
| $C_{19}$ | VH | VH | H | H | H |
| $C_{20}$ | H | H | H | H | H |
| $C_{21}$ | MH | MH | H | H | H |
| $C_{22}$ | H | H | H | H | H |
| $C_{23}$ | VH | VH | VH | VH | VH |
| $C_{24}$ | MH | H | H | H | H |
| $C_{25}$ | H | H | H | H | H |
| $C_{26}$ | VH | H | VH | H | VH |
| $C_{27}$ | H | H | H | H | H |
| $C_{28}$ | VH | VH | VH | VH | H |
| $C_{29}$ | H | H | H | H | H |
| $C_{30}$ | VH | H | VH | H | H |
| $C_{31}$ | H | H | H | H | VH |
| $C_{32}$ | H | H | H | H | VH |
| $C_{33}$ | VH | VH | H | H | H |
| $C_{34}$ | MH | H | H | H | H |
| $C_{35}$ | VH | H | H | H | VH |

Table 5.4: Ratings of 3PL provider alternatives with respect to criteria expressed by linguistic variables as given by the DMs

| Criteria | 3PL1 | | | | | 3PL2 | | | | | 3PL3 | | | | | 3PL4 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DM1 | DM2 | DM3 | DM4 | DM5 | DM1 | DM2 | DM3 | DM4 | DM5 | DM1 | DM2 | DM3 | DM4 | DM5 | DM1 | DM2 | DM3 | DM4 | DM5 |
| $C_1$ | F | MG | F | MG | MG | F | F | F | F | F | VP | VP | P | P | P | G | G | G | VG | G |
| $C_2$ | MG | MG | MG | MG | MG | MP | F | MP | MP | MP | P | P | P | P | P | G | G | G | G | G |
| $C_3$ | F | F | F | F | F | MG | F | F | F | F | MP | F | F | F | F | G | VG | G | VG | G |
| $C_4$ | MG | MG | MG | F | F | P | MP | MP | F | F | F | F | MP | MP | MP | MG | G | G | G | G |
| $C_5$ | F | F | F | F | F | MP | MP | MP | MP | MP | P | P | P | P | MP | G | G | VG | G | G |
| $C_6$ | MG | G | G | G | G | F | MP | MP | MP | F | F | F | F | F | F | G | G | G | G | G |
| $C_7$ | G | G | G | G | G | P | MP | MP | MP | P | F | F | F | F | F | G | G | G | G | G |
| $C_8$ | MG | G | MG | G | MG | F | MP | F | F | F | MP | MP | MP | MP | MP | VG | VG | G | G | G |
| $C_9$ | F | MG | F | F | F | MP | MP | MP | F | F | F | MP | F | MP | F | VG | G | VG | VG | VG |
| $C_{10}$ | F | F | F | F | F | F | F | F | F | F | F | F | F | F | F | G | G | G | G | G |
| $C_{11}$ | MG | F | F | F | F | MG | F | F | F | F | F | F | F | F | F | VG | G | VG | G | VG |
| $C_{12}$ | MG | MG | MG | F | F | MP | MP | P | MP | MP | MG | F | F | F | F | MG | MG | G | G | MG |
| $C_{13}$ | F | F | F | F | F | VP | VP | P | P | P | MP | F | MP | MP | MP | G | G | G | G | G |
| $C_{14}$ | G | G | MG | G | G | P | P | P | MP | MP | MP | MP | MP | MP | MP | VG | G | G | VG | VG |
| $C_{15}$ | G | G | G | G | G | MP | MP | MP | MP | F | F | F | F | F | MP | MG | MG | MG | G | G |
| $C_{16}$ | G | MG | G | MG | MG | F | F | F | F | F | F | F | F | F | F | G | G | G | G | G |
| $C_{17}$ | G | G | G | G | G | VP | VP | P | P | P | F | F | F | F | F | VG | G | VG | G | VG |
| $C_{18}$ | G | MG | MG | MG | MG | MP | P | MP | P | MP | MP | F | F | F | MP | G | G | G | G | G |
| $C_{19}$ | G | G | G | G | MG | F | F | F | MP | MP | P | MP | P | MP | MP | G | G | G | G | G |
| $C_{20}$ | F | MG | MG | MG | MG | MP | F | MP | F | MP | F | MP | MP | MP | MP | VG | G | VG | VG | VG |
| $C_{21}$ | F | F | F | F | F | F | F | F | F | F | F | F | F | MP | MP | MG | MG | G | G | G |
| $C_{22}$ | F | F | F | F | F | MG | MG | MG | F | F | MP | MP | MP | MP | MP | VG | G | G | VG | VG |
| $C_{23}$ | MG | MG | G | G | G | F | F | F | F | F | F | F | F | F | F | MG | MG | MG | MG | G |
| $C_{24}$ | G | G | MG | G | G | MG | F | F | F | F | F | F | F | F | F | G | G | G | G | G |
| $C_{25}$ | MG | MG | MG | G | G | MP | P | P | P | MP | MP | F | F | F | F | VG | VG | VG | G | VG |
| $C_{26}$ | G | G | G | G | G | F | F | F | F | MP | F | F | F | F | F | G | VG | G | VG | G |
| $C_{27}$ | MG | G | MG | G | MG | F | F | F | F | F | P | MP | F | MP | F | MG | MG | MG | MG | G |
| $C_{28}$ | F | F | F | F | F | MG | MG | MG | F | F | MP | MP | MP | MP | MP | G | G | G | G | G |
| $C_{29}$ | F | MG | F | MG | F | MG | MG | F | F | F | F | F | F | F | F | G | G | G | G | G |
| $C_{30}$ | F | F | F | F | F | MP | F | F | MP | F | MP | MP | P | P | P | VG | G | VG | G | G |
| $C_{31}$ | F | MG | MG | MG | F | F | F | F | F | F | F | F | F | F | F | G | G | G | G | G |
| $C_{32}$ | F | F | F | F | F | MP | F | MP | F | MP | MP | F | F | F | F | VG | G | G | G | G |
| $C_{33}$ | MG | F | MG | F | MG | F | F | F | F | F | MP | P | P | MP | P | G | G | G | G | G |
| $C_{34}$ | F | F | F | MP | MP | F | MG | F | MG | MG | F | F | F | MP | F | G | G | G | G | G |
| $C_{35}$ | MP | F | MP | F | MP | MG | MG | MG | F | F | F | F | F | F | F | G | G | G | VG | VG |

Table 5.5: Criteria weights and ratings of 3PL alternatives w.r.t. criteria expressed in grey numbers: Initial decision making matrix

| Criteria, $C_j$ | Weight | Ratings of 3PL alternatives expressed in grey numbers | | | |
|---|---|---|---|---|---|
| | $\otimes w_j$ | 3PL1 ($A_1$) | 3PL2 ($A_2$) | 3PL3 ($A_3$) | 3PL4 ($A_4$) |
| $C_1$ | (0.60,0.90) | (4.60,5.60) | (4.00,5.00) | (0.60,2.20) | (6.60,9.20) |
| $C_2$ | (0.72,0.94) | (5.00,6.00) | (3.20,4.20) | (1.00,3.00) | (6.00,9.00) |
| $C_3$ | (0.56,0.78) | (4.00,5.00) | (4.20,5.20) | (3.80,4.80) | (6.60,9.20) |
| $C_4$ | (0.64,0.86) | (4.60,5.60) | (3.00,4.20) | (3.40,4.40) | (5.80,8.40) |
| $C_5$ | (0.72,0.94) | (4.00,5.00) | (3.00,4.00) | (1.40,3.20) | (6.60,9.20) |
| $C_6$ | (0.66,0.92) | (5.80,8.40) | (3.40,4.40) | (4.00,5.00) | (6.00,9.00) |
| $C_7$ | (0.56,0.78) | (6.00,9.00) | (2.20,3.60) | (4.00,5.00) | (6.00,9.00) |
| $C_8$ | (0.60,0.90) | (5.40,7.20) | (3.80,4.80) | (3.00,4.00) | (7.20,9.40) |
| $C_9$ | (0.72,0.94) | (4.20,5.20) | (3.40,4.40) | (3.60,4.60) | (8.40,9.80) |
| $C_{10}$ | (0.78,0.96) | (4.00,5.00) | (4.00,5.00) | (4.00,5.00) | (6.00,9.00) |
| $C_{11}$ | (0.60,0.90) | (4.20,5.20) | (4.20,5.20) | (4.00,5.00) | (7.80,9.60) |
| $C_{12}$ | (0.60,0.90) | (4.60,5.60) | (2.60,3.80) | (4.20,5.20) | (5.40,7.20) |
| $C_{13}$ | (0.72,0.94) | (4.00,5.00) | (0.60,2.20) | (3.20,4.20) | (6.00,9.00) |
| $C_{14}$ | (0.60,0.90) | (5.80,8.40) | (1.80,3.40) | (3.00,4.00) | (7.80,9.60) |
| $C_{15}$ | (0.62,0.80) | (6.00,9.00) | (3.20,4.20) | (3.80,4.80) | (5.40,7.20) |
| $C_{16}$ | (0.50,0.64) | (5.40,7.20) | (4.00,5.00) | (4.00,5.00) | (6.00,9.00) |
| $C_{17}$ | (0.56,0.78) | (6.00,9.00) | (0.60,2.20) | (4.00,5.00) | (7.80,9.60) |
| $C_{18}$ | (0.6,0.9) | (5.20,6.60) | (2.20,3.60) | (3.60,4.60) | (6.00,9.00) |
| $C_{19}$ | (0.72,0.94) | (5.80,8.40) | (3.60,4.60) | (2.20,3.60) | (6.00,9.00) |
| $C_{20}$ | (0.60,0.90) | (4.80,5.80) | (3.40,4.40) | (3.20,4.20) | (8.40,9.80) |
| $C_{21}$ | (0.56,0.78) | (4.00,5.00) | (4.00,5.00) | (3.60,4.60) | (5.60,7.80) |
| $C_{22}$ | (0.60,0.90) | (4.00,5.00) | (4.60,5.60) | (3.00,4.00) | (7.80,9.60) |
| $C_{23}$ | (0.90,1.0) | (5.60,7.80) | (4.00,5.00) | (4.00,5.00) | (5.20,6.60) |
| $C_{24}$ | (0.58,0.84) | (5.80,8.40) | (4.20,5.20) | (4.00,5.00) | (6.00,9.00) |
| $C_{25}$ | (0.60,0.90) | (5.40,7.20) | (2.40,3.80) | (3.80,4.80) | (8.40,9.80) |
| $C_{26}$ | (0.78,0.96) | (6.00,9.00) | (3.80,4.80) | (4.00,5.00) | (7.20,9.40) |
| $C_{27}$ | (0.60,0.90) | (5.40,7.20) | (4.00,5.00) | (3.00,4.20) | (5.20,6.60) |
| $C_{28}$ | (0.84,0.98) | (4.00,5.00) | (4.60,5.60) | (3.00,4.00) | (6.00,9.00) |
| $C_{29}$ | (0.60,0.90) | (4.40,5.40) | (4.40,5.40) | (4.00,5.00) | (6.00,9.00) |
| $C_{30}$ | (0.72,0.94) | (4.00,5.00) | (3.60,4.60) | (2.40,3.80) | (7.20,9.40) |
| $C_{31}$ | (0.66,0.92) | (4.60,5.60) | (4.00,5.00) | (4.00,5.00) | (6.00,9.00) |
| $C_{32}$ | (0.66,0.92) | (4.00,5.00) | (3.40,4.40) | (3.80,4.80) | (6.60,9.20) |
| $C_{33}$ | (0.72,0.94) | (4.60,5.60) | (4.00,5.00) | (1.80,3.40) | (6.00,9.00) |
| $C_{34}$ | (0.58,0.84) | (3.60,4.60) | (4.60,5.60) | (3.80,4.80) | (6.00,9.00) |
| $C_{35}$ | (0.72,0.94) | (3.40,4.40) | (4.60,5.60) | (4.00,5.00) | (7.20,9.40) |

Table 5.6: Normalized decision making matrix

| Criteria, $C_j$ | Weight | Normalized ratings of 3PL alternatives expressed in grey numbers | | | |
|---|---|---|---|---|---|
| | $\otimes w_j$ | 3PL1 ($A_1$) | 3PL2 ($A_2$) | 3PL3 ($A_3$) | 3PL4 ($A_4$) |
| $C_1$ | (0.60,0.90) | (0.50,0.61) | (0.43,0.54) | (0.07,0.24) | (0.72,1.00) |
| $C_2$ | (0.72,0.94) | (0.56,0.67) | (0.36,0.47) | (0.11,0.33) | (0.67,1.00) |
| $C_3$ | (0.56,0.78) | (0.43,0.54) | (0.46,0.57) | (0.41,0.52) | (0.72,1.00) |
| $C_4$ | (0.64,0.86) | (0.55,0.67) | (0.36,0.50) | (0.40,0.52) | (0.69,1.00) |
| $C_5$ | (0.72,0.94) | (0.43,0.54) | (0.33,0.43) | (0.15,0.35) | (0.72,1.00) |
| $C_6$ | (0.66,0.92) | (0.64,0.93) | (0.38,0.49) | (0.44,0.56) | (0.67,1.00) |
| $C_7$ | (0.56,0.78) | (0.67,1.00) | (0.24,0.40) | (0.44,0.56) | (0.67,1.00) |
| $C_8$ | (0.60,0.90) | (0.57,0.77) | (0.40,0.51) | (0.32,0.43) | (0.77,1.00) |
| $C_9$ | (0.72,0.94) | (0.43,0.53) | (0.35,0.45) | (0.37,0.47) | (0.86,1.00) |
| $C_{10}$ | (0.78,0.96) | (0.44,0.56) | (0.44,0.56) | (0.44,0.56) | (0.67,1.00) |
| $C_{11}$ | (0.60,0.90) | (0.44,0.54) | (0.44,0.54) | (0.42,0.52) | (0.81,1.00) |
| $C_{12}$ | (0.60,0.90) | (0.64,0.78) | (0.36,0.53) | (0.58,0.72) | (0.75,1.00) |
| $C_{13}$ | (0.72,0.94) | (0.44,0.56) | (0.07,0.24) | (0.36,0.47) | (0.67,1.00) |
| $C_{14}$ | (0.60,0.90) | (0.60,0.88) | (0.19,0.35) | (0.31,0.42) | (0.81,1.00) |
| $C_{15}$ | (0.62,0.80) | (0.67,1.00) | (0.36,0.47) | (0.42,0.53) | (0.60,0.80) |
| $C_{16}$ | (0.50,0.64) | (0.60,0.80) | (0.44,0.56) | (0.44,0.56) | (0.67,1.00) |
| $C_{17}$ | (0.56,0.78) | (0.63,0.94) | (0.06,0.23) | (0.42,0.52) | (0.81,1.00) |
| $C_{18}$ | (0.6,0.9) | (0.58,0.73) | (0.24,0.40) | (0.40,0.51) | (0.67,1.00) |
| $C_{19}$ | (0.72,0.94) | (0.64,0.93) | (0.40,0.51) | (0.24,0.40) | (0.67,1.00) |
| $C_{20}$ | (0.60,0.90) | (0.49,0.59) | (0.35,0.45) | (0.33,0.43) | (0.86,1.00) |
| $C_{21}$ | (0.56,0.78) | (0.51,0.64) | (0.51,0.64) | (0.46,0.59) | (0.72,1.00) |
| $C_{22}$ | (0.60,0.90) | (0.42,0.52) | (0.48,0.58) | (0.31,0.42) | (0.81,1.00) |
| $C_{23}$ | (0.90,1.0) | (0.72,1.00) | (0.51,0.64) | (0.51,0.64) | (0.67,0.85) |
| $C_{24}$ | (0.58,0.84) | (0.64,0.93) | (0.47,0.58) | (0.44,0.56) | (0.67,1.00) |
| $C_{25}$ | (0.60,0.90) | (0.55,0.73) | (0.24,0.39) | (0.39,0.49) | (0.86,1.00) |
| $C_{26}$ | (0.78,0.96) | (0.64,0.96) | (0.40,0.51) | (0.43,0.53) | (0.77,1.00) |
| $C_{27}$ | (0.60,0.90) | (0.75,1.00) | (0.56,0.69) | (0.42,0.58) | (0.72,0.92) |
| $C_{28}$ | (0.84,0.98) | (0.44,0.56) | (0.51,0.62) | (0.33,0.44) | (0.67,1.00) |
| $C_{29}$ | (0.60,0.90) | (0.49,0.60) | (0.49,0.60) | (0.44,0.56) | (0.67,1.00) |
| $C_{30}$ | (0.72,0.94) | (0.43,0.53) | (0.38,0.49) | (0.26,0.40) | (0.77,1.00) |
| $C_{31}$ | (0.66,0.92) | (0.51,0.62) | (0.44,0.56) | (0.44,0.56) | (0.67,1.00) |
| $C_{32}$ | (0.66,0.92) | (0.43,0.54) | (0.37,0.48) | (0.41,0.52) | (0.72,1.00) |
| $C_{33}$ | (0.72,0.94) | (0.51,0.62) | (0.44,0.56) | (0.20,0.38) | (0.67,1.00) |
| $C_{34}$ | (0.58,0.84) | (0.40,0.51) | (0.51,0.62) | (0.42,0.53) | (0.67,1.00) |
| $C_{35}$ | (0.72,0.94) | (0.36,0.47) | (0.49,0.60) | (0.43,0.53) | (0.77,1.00) |

Table 5.7: Weighted normalized decision making matrix

| Criteria, $C_j$ | Weighted normalized ratings of 3PL alternatives expressed in grey numbers | | | |
|---|---|---|---|---|
| | 3PL1 ($A_1$) | 3PL2 ($A_2$) | 3PL3 ($A_3$) | 3PL4 ($A_4$) |
| $C_1$ | (0.30,0.55) | (0.26,0.49) | (0.04,0.22) | (0.43,0.90) |
| $C_2$ | (0.40,0.63) | (0.26,0.44) | (0.08,0.31) | (0.48,0.94) |
| $C_3$ | (0.24,0.42) | (0.26,0.44) | (0.23,0.41) | (0.40,0.78) |
| $C_4$ | (0.35,0.57) | (0.23,0.43) | (0.26,0.45) | (0.44,0.86) |
| $C_5$ | (0.31,0.51) | (0.23,0.41) | (0.11,0.33) | (0.52,0.94) |
| $C_6$ | (0.43,0.86) | (0.25,0.45) | (0.29,0.51) | (0.44,0.92) |
| $C_7$ | (0.37,0.78) | (0.14,0.31) | (0.25,0.43) | (0.37,0.78) |
| $C_8$ | (0.34,0.69) | (0.24,0.46) | (0.19,0.38) | (0.46,0.90) |
| $C_9$ | (0.31,0.50) | (0.25,0.42) | (0.26,0.44) | (0.62,0.94) |
| $C_{10}$ | (0.35,0.53) | (0.35,0.53) | (0.35,0.53) | (0.52,0.96) |
| $C_{11}$ | (0.26,0.49 | (0.26,0.49) | (0.25,0.47) | (0.49,0.90) |
| $C_{12}$ | (0.38,0.70) | (0.22,0.48) | (0.35,0.65) | (0.45,0.90) |
| $C_{13}$ | (0.32,0.52) | (0.05,0.23) | (0.26,0.44) | (0.48,0.94) |
| $C_{14}$ | (0.36,0.79) | (0.11,0.32) | (0.19,0.38) | (0.49,0.90) |
| $C_{15}$ | (0.41,0.80) | (0.22,0.37) | (0.26,0.43) | (0.37,0.64) |
| $C_{16}$ | (0.30,0.51) | (0.22,0.36) | (0.22,0.36) | (0.33,0.64) |
| $C_{17}$ | (0.35,0.73) | (0.04,0.18) | (0.23,0.41) | (0.46,0.78) |
| $C_{18}$ | (0.35,0.66 | (0.15,0.36) | (0.24,0.46) | (0.40,0.90) |
| $C_{19}$ | (0.46,0.88 | (0.29,0.48) | (0.18,0.38) | (0.48,0.94) |
| $C_{20}$ | (0.29,0.53) | (0.21,0.40) | (0.20,0.39) | (0.51,0.90) |
| $C_{21}$ | (0.29,0.50) | (0.29,0.50) | (0.26,0.46) | (0.40,0.78) |
| $C_{22}$ | (0.25,0.47) | (0.29,0.53) | (0.19,0.38) | (0.49,0.90) |
| $C_{23}$ | (0.65,1.00) | (0.46,0.64) | (0.46,0.64) | (0.60,0.85) |
| $C_{24}$ | (0.37,0.78) | (0.27,0.49) | (0.26,0.47) | (0.39,0.84) |
| $C_{25}$ | (0.33,0.66) | (0.15,0.35) | (0.23,0.44) | (0.51,0.90) |
| $C_{26}$ | (0.50,0.92) | (0.32,0.49) | (0.33,0.51) | (0.60,0.96) |
| $C_{27}$ | (0.45,0.90) | (0.33,0.63) | (0.25,0.53) | (0.43,0.83) |
| $C_{28}$ | (0.37,0.54) | (0.43,0.61) | (0.28,0.44) | (0.56,0.98) |
| $C_{29}$ | (0.29,0.54) | (0.29,0.54) | (0.27,0.50) | (0.40,0.90) |
| $C_{30}$ | (0.31,0.50) | (0.28,0.46) | (0.18,0.38) | (0.55,0.94) |
| $C_{31}$ | (0.34,0.57) | (0.29,0.51) | (0.29,0.51) | (0.44,0.92) |
| $C_{32}$ | (0.29,0.50) | (0.24,0.44) | (0.27,0.48) | (0.47,0.92) |
| $C_{33}$ | (0.37,0.58) | (0.32,0.52) | (0.14,0.36) | (0.48,0.94) |
| $C_{34}$ | (0.23,0.43) | (0.30,0.52) | (0.24,0.45) | (0.39,0.84) |
| $C_{35}$ | (0.26,0.44) | (0.35,0.56) | (0.31,0.50) | (0.55,0.94) |

Table 5.8: Partial matrices of dominance

| Criteria | Dominance between the alternatives (with respect to individual criterion) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $[A_1, A_2]$ | $[A_1, A_3]$ | $[A_1, A_4]$ | $[A_2, A_1]$ | $[A_2, A_3]$ | $[A_2, A_4]$ | $[A_3, A_1]$ | $[A_3, A_2]$ | $[A_3, A_4]$ | $[A_4, A_1]$ | $[A_4, A_2]$ | $[A_4, A_3]$ |
| $C_1$ | 0.05 | 0.30 | 0.27 | 0.05 | 0.25 | 0.31 | 0.30 | 0.25 | -0.56 | 0.27 | 0.31 | -0.56 |
| $C_2$ | 0.17 | 0.32 | 0.23 | 0.17 | 0.15 | 0.39 | 0.32 | 0.15 | -0.53 | 0.23 | 0.39 | -0.53 |
| $C_3$ | 0.01 | 0.01 | 0.28 | 0.01 | 0.03 | 0.26 | 0.01 | 0.03 | 0.29 | 0.28 | 0.26 | 0.29 |
| $C_4$ | 0.13 | 0.11 | 0.21 | 0.13 | 0.03 | 0.34 | 0.11 | 0.03 | 0.32 | 0.21 | 0.34 | 0.32 |
| $C_5$ | 0.09 | 0.19 | 0.34 | 0.09 | 0.11 | 0.43 | 0.19 | 0.11 | -0.52 | 0.34 | 0.43 | -0.52 |
| $C_6$ | 0.31 | 0.26 | 0.04 | 0.31 | 0.05 | 0.36 | 0.26 | 0.05 | 0.31 | 0.04 | 0.36 | 0.31 |
| $C_7$ | 0.37 | 0.26 | 0.00 | 0.37 | 0.12 | 0.37 | 0.26 | 0.12 | 0.26 | 0.00 | 0.37 | 0.26 |
| $C_8$ | 0.18 | 0.24 | 0.17 | 0.18 | 0.07 | 0.35 | 0.24 | 0.07 | 0.41 | 0.17 | 0.35 | 0.41 |
| $C_9$ | 0.07 | 0.05 | 0.38 | 0.07 | 0.02 | 0.45 | 0.05 | 0.02 | 0.43 | 0.38 | 0.45 | 0.43 |
| $C_{10}$ | 0.00 | 0.00 | 0.33 | 0.00 | 0.00 | 0.33 | 0.00 | 0.00 | 0.33 | 0.33 | 0.33 | 0.33 |
| $C_{11}$ | 0.00 | 0.02 | 0.33 | 0.00 | 0.02 | 0.33 | 0.02 | 0.02 | 0.35 | 0.33 | 0.33 | 0.35 |
| $C_{12}$ | 0.20 | 0.04 | 0.15 | 0.20 | 0.16 | 0.34 | 0.04 | 0.16 | 0.19 | 0.15 | 0.34 | 0.19 |
| $C_{13}$ | 0.28 | 0.07 | 0.32 | 0.28 | 0.21 | -0.59 | 0.07 | 0.21 | 0.39 | 0.32 | -0.59 | 0.39 |
| $C_{14}$ | 0.38 | 0.32 | 0.12 | 0.38 | 0.07 | 0.49 | 0.32 | 0.07 | 0.43 | 0.12 | 0.49 | 0.43 |
| $C_{15}$ | 0.33 | 0.28 | 0.12 | 0.33 | 0.05 | 0.22 | 0.28 | 0.05 | 0.17 | 0.12 | 0.22 | 0.17 |
| $C_{16}$ | 0.12 | 0.12 | 0.09 | 0.12 | 0.00 | 0.22 | 0.12 | 0.00 | 0.22 | 0.09 | 0.22 | 0.22 |
| $C_{17}$ | 0.45 | 0.24 | 0.08 | 0.45 | 0.21 | 0.52 | 0.24 | 0.21 | 0.31 | 0.08 | -0.52 | 0.31 |
| $C_{18}$ | 0.25 | 0.16 | 0.17 | 0.25 | 0.10 | 0.42 | 0.16 | 0.10 | 0.33 | 0.17 | 0.42 | 0.33 |
| $C_{19}$ | 0.31 | 0.41 | 0.05 | 0.31 | 0.11 | 0.35 | 0.41 | 0.11 | 0.45 | 0.05 | 0.35 | 0.45 |
| $C_{20}$ | 0.11 | 0.12 | 0.30 | 0.11 | 0.02 | 0.41 | 0.12 | 0.02 | 0.43 | 0.30 | 0.41 | 0.43 |

Table 5.8 (continued): Partial matrices of dominance

| Criteria | Dominance between the alternatives (with respect to individual criterion) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $[A_1, A_2]$ | $[A_1, A_3]$ | $[A_1, A_4]$ | $[A_2, A_1]$ | $[A_2, A_3]$ | $[A_2, A_4]$ | $[A_3, A_1]$ | $[A_3, A_2]$ | $[A_3, A_4]$ | $[A_4, A_1]$ | $[A_4, A_2]$ | $[A_4, A_3]$ |
| $C_{21}$ | 0.00 | 0.03 | 0.21 | 0.00 | 0.03 | 0.21 | 0.03 | 0.03 | 0.25 | 0.21 | 0.21 | 0.25 |
| $C_{22}$ | 0.05 | 0.08 | 0.35 | 0.05 | 0.13 | 0.30 | 0.08 | 0.13 | 0.43 | 0.35 | 0.30 | 0.43 |
| $C_{23}$ | 0.29 | 0.29 | 0.11 | 0.29 | 0.00 | 0.17 | 0.29 | 0.00 | 0.17 | 0.11 | 0.17 | 0.17 |
| $C_{24}$ | 0.22 | 0.24 | 0.04 | 0.22 | 0.02 | 0.26 | 0.24 | 0.02 | 0.28 | 0.04 | 0.26 | 0.28 |
| $C_{25}$ | 0.26 | 0.17 | 0.21 | 0.26 | 0.09 | 0.47 | 0.17 | 0.09 | 0.38 | 0.21 | 0.47 | 0.38 |
| $C_{26}$ | 0.33 | 0.31 | 0.08 | 0.33 | 0.02 | 0.39 | 0.31 | 0.02 | 0.37 | 0.08 | 0.39 | 0.37 |
| $C_{27}$ | 0.21 | 0.30 | 0.05 | 0.21 | 0.09 | 0.16 | 0.30 | 0.09 | 0.25 | 0.05 | 0.16 | 0.25 |
| $C_{28}$ | 0.06 | 0.10 | 0.34 | 0.06 | 0.16 | 0.28 | 0.10 | 0.16 | 0.43 | 0.34 | 0.28 | 0.43 |
| $C_{29}$ | 0.00 | 0.03 | 0.27 | 0.00 | 0.03 | 0.27 | 0.03 | 0.03 | 0.30 | 0.27 | 0.27 | 0.30 |
| $C_{30}$ | 0.04 | 0.12 | 0.36 | 0.04 | 0.09 | 0.39 | 0.12 | 0.09 | 0.47 | 0.36 | 0.39 | 0.47 |
| $C_{31}$ | 0.05 | 0.05 | 0.26 | 0.05 | 0.00 | 0.31 | 0.05 | 0.00 | 0.31 | 0.26 | 0.31 | 0.31 |
| $C_{32}$ | 0.05 | 0.02 | 0.32 | 0.05 | 0.03 | 0.38 | 0.02 | 0.03 | 0.34 | 0.32 | 0.38 | 0.34 |
| $C_{33}$ | 0.06 | 0.23 | 0.26 | 0.06 | 0.17 | 0.32 | 0.23 | 0.17 | 0.48 | 0.26 | 0.32 | 0.48 |
| $C_{34}$ | 0.08 | 0.02 | 0.31 | 0.08 | 0.06 | 0.23 | 0.02 | 0.06 | 0.29 | 0.31 | 0.23 | 0.29 |
| $C_{35}$ | 0.11 | 0.05 | 0.41 | 0.11 | 0.05 | 0.30 | 0.05 | 0.05 | 0.36 | 0.41 | 0.30 | 0.36 |

Table 5.9: Final matrices of dominance

| Alternatives | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0.00 | 5.62 | 5.59 | 7.55 |
| $A_2$ | 5.62 | 0.00 | 2.73 | 10.73 |
| $A_3$ | 5.59 | 2.73 | 0.00 | 9.11 |
| $A_4$ | 7.55 | 9.69 | 9.11 | 0.00 |

Table 5.10: Global dominance value and corresponding ranking order

| Alternatives | $\delta$ | $\xi$ | Ranking order (Obtained in the proposed approach) |
|---|---|---|---|
| $A_1$ | 18.76 | 0.15 | 3 |
| $A_2$ | 19.08 | 0.18 | 2 |
| $A_3$ | 17.43 | 0.00 | 4 |
| $A_4$ | 26.36 | 1.00 | 1 |

Table 5.11: Separation measure of each alternative with respect to positive ideal and negative ideal solution: Computation of closeness coefficient and corresponding ranking order

| Alternatives | $d_i^+$ | $d_i^-$ | $C_i^+$ | Ranking order (Obtained grey-TOPSIS) |
|---|---|---|---|---|
| $A_1$ | 7.27 | 6.63 | 0.48 | 2 |
| $A_2$ | 12.19 | 1.65 | 0.12 | 3 |
| $A_3$ | 12.59 | 1.21 | 0.09 | 4 |
| $A_4$ | 0.28 | 13.49 | 0.98 | 1 |

# Chapter 6

# Evaluation of Supply Chain's Ecosilient (G-Resilient) Performance Index: A Fuzzy Embedded Decision Support Framework

## 6.1 Coverage

Recently, in turbulent and highly competitive global marketplace, organizational sustainability in long run necessitates adaptation to appropriate Supply Chain (SC) strategies. Hence, traditional supply chain philosophies are being restructured nowadays to fulfill different business goals. Articulation of lean, agile, green and resilient supply chain strategies could be found in literature; however, it is felt that integration of those in various modes may definitely improve overall supply chain's performance.

Lean Supply Chain (LSC) focuses on minimization of industrial 'wastes'; whereas, Agile Supply Chain (ASC) enables the organization to respond fast in the situations of sudden changes in demand/supply or customer preferences. Leagile is a 'hybrid' supply chain philosophy of lean and agile systems; discussed in literature. On the contrary, in order to make the supply chain environment friendly; green paradigm (i.e. Green Supply Chain; GSC) has come into picture. Additionally to cope up with the effects of disturbances/disruption situation within the system; the concept of Resilient Supply Chain (RSC) has been introduced. Resiliency in supply chain is the ability to recover to the desired (stable) state after a disruption occurs. Past researchers have focused on integration of lean, agile and green paradigm together to ensure an efficient supply chain construct. But the integration of green and resilient paradigm has been found rarely reported in the literature.

To deal with the unexpected situations/disturbances in the supply chain management along with embedded environmental consciousness, an attempt has been made herein to integrate the resilient supply chain and green supply chain philosophies; thereof to evaluate of a supply chain ‘g-resilient’/ ‘ecosilient’ Index for a case automotive company. A consolidated list consisting of Supply Chain Practices (SCP) (combining green and resilient performance indices) have been articulated in this study. A decision making group has been assumed; where, the role of Decision-Makers’ (DMs’) has been to provide individuals’ judgment towards determining the weight and the rating (performance extent) of various performance indices.

Qualitative information as acquired from the decision making group being in the form of natural language representation; application of fuzzy set theory has been found suitable to deal with the inherent ambiguity and vagueness of the decision making data. A case automotive company located at the southern part of India has been considered as a part of this empirical study.

The overall g-resilient supply chain performance has been determined by computing a unique ecosilient (g-resilient) index. The concepts of Fuzzy Performance Importance Index (FPII) along with Degree of Similarity (DOS) adopted from fuzzy set theory have been applied to rank various performance indicators. By exploring the concept of fuzzy DOS, outlined in the trapezoidal fuzzy numbers set theory, various supply chain performance indicators have been classified into three distinct performance categories/levels (viz. regretful, tolerable, and satisfactory). Such categorization has been found helpful in order to determine ill (poor) performing supply chain areas, which need future improvement towards boosting up overall g-resilient index of the company’s supply chain. In addition to that, the interrelationships amongst various g-resilient indices (performance indicators) have also been established through Interpretive Structural Modeling (ISM).

## 6.2 Background and Problem Statement

Many authors defined Supply Chain Management (SCM) in light of operational terms including the flow of materials and products; others interpreted SCM as a management philosophy; whilst, few viewed it as a management process (Tyndall et al. 1998; Mentzer et al., 2001). Christopher (2016) defined the supply chain as a network of organizations involved together through upstream and downstream linkages, in the different process and activities, to produce value in the form of products and services to the hand of the ultimate consumer. Stevens (1989) defined that the objective of managing the supply chain is to coordinate the requirements of the customer with the flow of materials from suppliers to maintain a balance between conflicting goals of high customer service, low inventory management, and low unit (product) cost. In general, supply chain is a network of activities, information, society and organization, primarily focused to move a product and service to the end user. This sort of relationship usually involve three major functions; namely,

a) Procurement of raw material,
b) Transformation of raw material into finished product and finally,
c) Delivery of finished goods over a network of wholesalers and retailers to the end user.

Lambert et al. (1998) defined a supply chain as the alignment of firms that brings products or services to the market. However, such alignment comprises inherent risks because of many reasons like uneven customer demand, variation in the time of travel and the breakdown of machines/vehicles at certain situations. Recent trends of supply chain philosophies encourage increased rate of outsourcing, offshoring, adaptation to lean, green and agile manufacturing practices. However, these philosophies mainly focus on reducing supply chain cost without bothering inherent risks in supply chain management. Hence, an effective supply chain management policy is indeed a requirement to balance the demand and supply with possible reduction of risk and uncertainties in an enthusiastic manner.

Risk is a probability or threat of damage, injury, loss, or any other negative incident caused by external or internal vulnerabilities which can be avoided through preemptive action and adaptation to ‘resilient’ supply chain management philosophies. In this context, it is to be noted that ‘risk’ is somewhat different from ‘uncertainty’; as risk is a controllable factor and where outcomes are known while in the case of uncertainty outcomes are unknown and uncontrollable.

Typically, traditional supply chain was maintained (managed) overlooking environmental impact during the entire manufacturing and the distribution process; which might cause substantial hazard to the environment. With passage of timers, environmental pollution (due to the generation of huge non-biodegradable wastes like plastic materials, metal scraps, hazardous chemicals etc.) and the global warming (increase of Earth's average surface temperature due to effect of greenhouse gases, such as carbon dioxide emissions from burning fossil fuels) have increased drastically; consequently, consumers have changed their habit of buying, and looking for a product that can be recyclable, reusable and disposable to protect the environment. Strict guidelines of the Government and the strong consumer pressure have enforced the industries to adopt environment-friendly manufacturing process i.e. to follow ‘green practices’ in every stage of the supply chain management. Afterward, the ‘green’ consciousness has been taken into account to save the environment and hence, traditional supply chain management has reoriented as Green Supply Chain Management (GSCM). The concept of GSCM is to integrate environmental thinking into supply chain management (Chin et al., 2015).

It is, hereby, experienced that nowadays most of the organizations have moved towards the sustainable supply chain to reduce the total carbon footprint emitted through various industrial activities like cement production, deforestation as well as the burning of fossil fuels like coal, oil and natural gas. The sustainable supply chain philosophy and the practices delineated therein must be followed right from product design and development to the material selection, manufacturing, packaging, transportation, warehousing, distribution, consumption, return, and disposal (Linton et al. 2007; Walker et al., 2008; Büyüközkan and Çifçi, 2011).

Christopher and Peck (2004) developed a resilient supply chain approach defining resilient paradigm focusing the supply chain ability to recover to the desired state after a disruption occurs. Resiliency in engineering can be defined as the tendency of a material to return to its original shape after the removal of a stress that has produced elastic strain (Merriam-Webster 2007). In industrial context, the resiliency is an adaptive control term; where, managers maintain a system for the recovery of the organization after any unexpected event or demand by promising the continuity of the operation at the best possible rate. However, Pettit et al. (2010) remarked that following a disruption it may not be beneficial for a supply chain to return to its original shape; but rather to learn from the disturbance and adapt a new configuration that may prevent the future disturbances. Resilient supply chains may not be the lowest-cost supply chains; but, they tend to be more capable of surviving with the uncertainty of the business environment (Govindan et al., 2015).

Thus, supply chain resilience is supposed to be a highly desirable network, as it escalates a firm's readiness in dealing with risks that can appear from the customers' side, the suppliers' side, the internal processes adopted or from the supply chain integration mechanisms employed (Purvis et al., 2016). Chan and Qi (2003) applied a process-based systematic perspective approach in light of fuzzy set theory to build an effective model to measure the holistic performance of complex supply chains. Lin et al. (2006) developed a Fuzzy Agility Index (FAI) based on supply chain agility providers using fuzzy logic. In this paper supply chain agility was defined how fast a supply chain responds to the changes in environment, customer preferences, competitive forces etc. In broad term, agility can be understood as means for handling change, increasing customer responsiveness, and mastering market turbulence (Van Hoek et al., 2001).

Yang (2009) proposed a performance evaluation index system to examine the efficiency and the benefits of supply chain. An enhanced Balanced Scorecards (BSC) was developed therein. In this paper, fuzzy logic approach was recognized as an effective way in determining the uncertainty and ambiguity in evaluating supply chain performance extent (Olugu and Wong, 2009). Cao and Chen (2010) established a performance evaluation approach by applying fuzzy comprehensive evaluation system to measure the performance of green supply chain. Author further used a grey incidence analysis to examine the results obtained thereof to provide scientific evidences for improvement of the green supply chain. Sun (2010) developed an evaluation model based on fuzzy-AHP (Analytic Hierarchy Process) and fuzzy-TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) in order to assist supply chain performance measurement. Lin and Li (2010) proposed an integrated framework for supply chain performance measurement by employing the six-sigma metrics in order to obtain a more comprehensive coverage of performance requisites. El-Baz (2011) presented a performance measurement approach based on fuzzy set theory and the pair-wise comparison of AHP. In the anticipated model, various input factors (new product design, process design, distributed cost, inventory cost, customer response, on-time delivery, efficiency, accuracy, product quality etc.) were treated. Behrouzi and Wong (2011) presented a method to measure the lean performance of manufacturing systems by applying fuzzy membership functions. Govindan et al. (2013) applied a fuzzy multi-criteria methodology for determining the sustainability performance of a supplier based on triple bottom line approach. Olugu and Wong (2012) explored an expert fuzzy rule-based system for performance evaluation using a study executed in a case automotive industry (Malaysia). Khalili-Damghani and Tavana (2013) developed a Fuzzy Network Data Envelopment Analysis (NDEA) model for determining the performance of agile supply chains.

Lin (2013) used a fuzzy DEMATEL (Decision-Making Trial and Evaluation Laboratory) approach to evaluate the green supply chain management practices. The authors noticed the following influential factors in the context of green supply chain activities, viz. practices, performances, and external pressures. Bhattacharya et al. (2014) applied a fuzzy-ANP based balanced scorecard in combination with an intra-organizational collaborative decision-making (CDM) towards the measurement of green supply chain performance. Afterward, a green causal relationship was formed and linked to the fuzzy-ANP (Analytical Network Process) approach.

Despite the relevancy of the topic, it has been found that still there exists research gap of developing an integrated assessment framework in a supply chain perspective; whose, focus is exclusively on the deployment of green and resilient paradigms simultaneously. Natarajarathinam et al. (2009) emphasized the need on developing scales for estimating supply chain resilience. Mollenkopf et al. (2010) also stated that there is a lack of integrated metrics and measurement methods that cover green strategies throughout the supply chain. Therefore, the main objective of current work is to propose an integrated performance evaluation index system combining green as well as resiliency practices and thereby to compute a unique performance index (ecosilient/g-resilient index) to infer the extent of successful adaptation/execution of resilience and green philosophies, simultaneously, embedded in the supply chain activities in relation to a case company; considered as a part of this empirical research.

The specific objectives of the present work have been pointed out below.

1. To develop an integrated decision support framework to facilitate g-resilient supply chain performance evaluation.
2. To determine supply chain’s ‘ecosilient/g-resilient’ index.
3. To categorize various g-resilient performance indices (supply chain practices) in accordance with their current performance status.
4. To understand the interrelationship among various g-resilient performance indices.

## 6.3 Research Methodology

### 6.3.1 Fuzzy Preliminaries

In decision making involving quantitative criteria values, objective (numeric) information can be dealt easily through conventional Multi-Criteria Decision Making (MCDM) methods; whereas, in decision making involving subjective criteria, subjective (qualitative) information cannot be utilized until and unless they are converted into some scientific values (Chou et al., 2008). For doing so, (Zadeh, 1965) introduced fuzzy set theory, that has the capability to cope up with inherent ambiguity and vagueness of linguistic human judgment during complex decision making problems. Zimmermann (2010) also stated that fuzzy set theory provides a strict scientific system through which precarious information can be converted into a unified scale precisely. Moreover, it can also be treated as a modeling terminology, strongly recommended for circumstances where fuzzy relationship, criteria, and phenomena exist.

Operational rules of any two positive trapezoidal fuzzy numbers $\tilde{a} = (a_1, a_2, a_3, a_4)$ and $\tilde{b} = (b_1, b_2, b_3, b_4)$ could be articulated from the reporting by (Chen and Chen, 2007)

**Definition 1**: Let, two trapezoidal fuzzy numbers $\tilde{a} = (a_1, a_2, a_3, a_4)$ and $\tilde{b} = (b_1, b_2, b_3, b_4)$ then the operation with these fuzzy numbers are defined as follows:

**1. Addition of fuzzy numbers (+)**

$$\tilde{a} \oplus \tilde{b} = (a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4) \tag{6.1}$$

**2. Subtraction of fuzzy numbers (-)**

$$\tilde{a}(-)\tilde{b} = (a_1 - b_1, a_2 - b_2, a_3 - b_3, a_4 - b_4) \tag{6.2}$$

**3. Multiplication of fuzzy numbers** $(\otimes)$

$$\tilde{a} \otimes \tilde{b} = (a_1 b_1, a_2 b_2, a_3 b_3, a_4 b_4) \tag{6.3}$$

**4. Division of fuzzy numbers** $(/)$

$$\tilde{a}(/)\tilde{b} = (a_1 / b_4, a_2 / b_3, a_3 / b_2, a_4 / b_1) \tag{6.4}$$

**5. Multiplication by a scalar number** $k$

$$k\tilde{a} = (ka_1, ka_2, ka_3, ka_4) \quad (6.5)$$

**Definition 2**: Let a trapezoidal fuzzy number $\tilde{a} = (a_1, a_2, a_3, a_4)$ then the defuzzified (i.e. crisp) value $m(\tilde{a})$ is calculated by:

$$m(\tilde{a}) = \frac{(a_1 + a_2 + a_3 + a_4)}{4} \quad (6.6)$$

**Definition 3**: **Degree of Similarity (DOS)**

Degree of Similarity (DOS) between two generalized trapezoidal fuzzy number (GTFNs) $\tilde{A} = (a_1, a_2, a_3, a_4)$ and $\tilde{B} = (b_1, b_2, b_3, b_4)$ can be articulated from the paper by (Hsieh and Chen, 1999).

$$S(\tilde{A}, \tilde{B}) = \frac{1}{1 + d(\tilde{A}, \tilde{B})} \quad (6.7)$$

Here, $d(\tilde{A}, \tilde{B}) = |P(\tilde{A}) - P(\tilde{B})|$

$$P(\tilde{A}) = \frac{a_1 + a_2 + a_3 + a_4}{6}, \; P(\tilde{B}) = \frac{b_1 + b_2 + b_3 + b_4}{6}$$

### 6.3.2 Interpretive Structural Modeling (ISM): Theoretical Basis

Interpretive Structural Modeling (ISM) is a well developed methodology for recognizing relationships among specific items, which define a problem or an issue. The ISM has been progressively used by previous researchers to characterize the interrelationships amongst several elements associated to the subject. Interpretive Structural Modeling (ISM) is an interactive learning process. The process is often used to decide the relationship between the items. ISM provides solutions for complex problems through communication, conversation, and discussion. The ISM was first developed by (Warfield, 1974) to create a unique structural mapping of complex interconnections of elements. Its basic idea is to utilize experts' practical experience and knowledge in real world situations to decompose an intricate system into several elements and thus to form a multi-level structural model (Warfield, 1976). ISM can also be applied successfully to recognize and summarize relationships amongst specific variables creating or defining a problem or an issue (Warfield, 1974; Sage, 1977). (Szyperski and Eul-Bischoff, 1983) represented the basic concept of the ISM (Fig. 6.1).

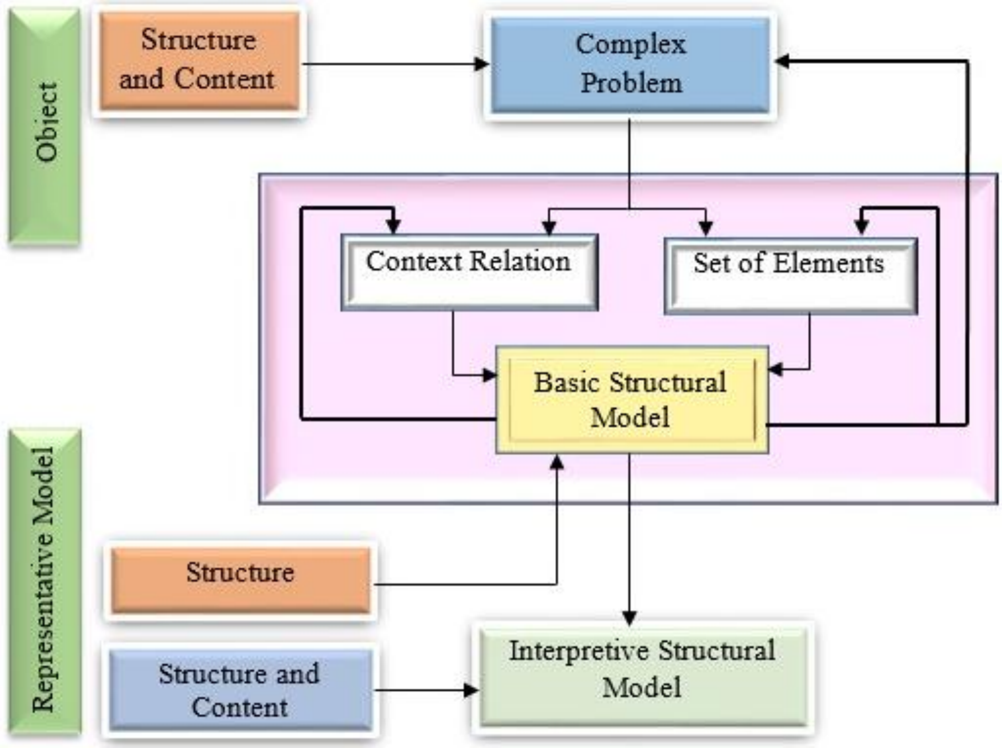


Fig. 6.1: Block diagram represent ISM approach

In Fig. 6.1 maximum possible iterations were shown by bold lines. In this part of work, ISM has been applied to help in visualizing the interrelationships amongst supply chain performance indices according to their driver and dependence power. Application potential of ISM approach can be understood well through survey of past literature. Mandal and Deshmukh (1994) identified the following vendor selection criteria viz. quality, delivery, production facilities, technical capability, after-sales service, labor relations etc. and established interrelationships amongst them through ISM approach. Thakkar et al. (2005) presented a hybrid approach by integrating the ISM approach and Analytic Network Process (ANP) together for the third party logistics (3PL) service provider selection problem. Kannan et al. (2008) proposed ISM and AHP to select the green suppliers for a case automobile company.

Kannan et al. (2009) developed a hybrid decision making framework (through exploration of ISM and fuzzy-TOPSIS) to support the selection process of the best third party reverse logistic provider (3PRLP) selection. Singh et al. (2010) applied interpretive structural modeling for selection of best supply chain practices for a case automobile company. Azevedo et al. (2013a) proposed a decision making framework based on ISM approach to identify and rank a set of supply chain performance measures (criteria) for an automotive case company. Mangla et al. (2014b) provided an ISM-based approach to implement and to initiate green activities in supply chain management.

Sivaprakasam et al. (2015) developed a strategic decision making tool using ISM framework for a textile manufacturing industry, to analyze the criteria involved in the implementation of green supply chain management. Girubha et al. (2016) also applied ISM approach integrated with Analytic Network Process (ANP) and ELECTRE II (*Elimination and Et Choice Translating Reality*) process in relation to the sustainable supplier selection problem.

#### 6.3.2.1 Procedural Steps

The various steps involved in ISM technique have been given as follow (Mandal and Deshmukh, 1994; Warfield, 1994, Govindan et al., 2012; Azevedo et al., 2013a):

**Step 1: Selection of Elements Relevant to the Problem**

The very first step of ISM methodology is to investigate the relevant elements and their association with the current problem context. This step can be performed through brainstorming, survey, group discussion, interviews etc.

**Step 2: Establishing Contextual Relation Type**

Next, the appropriate relation must be cogently stated as a possible statement of relationship amongst the elements. Relations may be of several types like comparative, influence, neutral or temporal relations.

**Step 3: Construction of Structural Self-Interaction Matrix (SSIM)**

This is the most important and demanding phase of ISM methodology where the contextual relationship among the risk factors based on experts opinion is incorporated. Keeping in mind the contextual relationship for each element, the existence of a relation between any two sub-elements ($i$ and $j$) and the associated direction of the relation is questioned. Thereafter, the participants decide upon pairwise relationship between two elements (factors).

Four symbols are commonly used to denote the direction of the relationship between the elements $i$ and $j$:

V – For the relation from $i$ to $j$ but not in both directions;

A – For the relation from $j$ to $i$ but not in both directions;

X – For both direction relations from $i$ to $j$ and $j$ to $i$; and

O – If the relation between the elements does not appear to be valid.

**Step 4: Developing A Reachability Matrix From the SSIM and Checking For Transitivity**

This step is concerned about the construction of the reachability matrix M. It is a binary matrix since the entry V, A, X and O of the SSIM are transformed into 1 and 0 as per the given rules:

I. If the $(i, j)$ entry in the SSIM is V, then the $(i, j)$ entry in the reachability matrix becomes 1 and the $(j, i)$ entry becomes 0.

II. If the $(i, j)$ entry in the SSIM is A, then the $(i, j)$ entry in the reachability matrix becomes 0 and the $(j, i)$ ) entry becomes 1.

III. If the $(i, j)$ entry in the SSIM is X, then both the $(i, j)$ and $(j, i)$ entries of the reachability matrix become 1.

IV. If the $(i, j)$ entry of the SSIM is O, then both the $(i, j)$ and $(j, i)$ entries of the reachability matrix become 0.

Transitivity is a basic assumption in ISM that leads to the final reachability matrix. It states that if element A is related to B, and B is related to C; it may be inferred that A is related to C. If element $(i, j)$ of the final reachability matrix is zero, there will not be any direct as well as indirect relationships from element $i$ to element $j$. The initial reachability matrix may not have this characteristic because when there is no direct but an indirect relationship from element $i$ to $j$, entry $(i, j)$ is also zero. Indirect relationships can be found by raising the initial reachability matrix (with diagonal entries set to 1) to successive powers until no new entries are obtained (Malone, 1975).

**Step 5: Level Partitioning of Reachability Matrix**

This phase includes extraction of a hierarchical ordering from the reachability matrix by level partitioning (Warfield, 1974). The key focus of this step is to facilitate the construction of the digraph from the reachability matrix. The level partition makes use of sets associated with each element $S_j$ in $S$. The reachability set $R(s_i)$ consists of the element itself and other elements which are reachable from $S_i$. In the same way, there may be some elements which can reach the element $S_i$ constituting the antecedent set $A(s_i)$. Subsequently, an intersection of the reachability set and antecedent set $(R(s_i) \cap A(s_i))$, i.e. the common elements in both sets, is formed for each element. The element for which $R(s_i) = (R(s_i) \cap A(s_i))$ is treated as the top-level element in the ISM hierarchy. The top-level element has no relation to any other elements above their own level. Once top-level elements are acknowledged, they are separated out from the other elements. Then, the same process undertakes successive iterations till the level of all elements is attained. These recognized levels help in building the digraph and final ISM model.

**Step 6: MICMAC Analysis**

The abbreviation of MICMAC is the '*Matrice d'Impacts croises-multipication appliqué an classment*' means cross-impact matrix multiplication applied to classification (Sharma et al., 1995). MICMAC analysis is a part of structural analysis which aims to identify the most important variables of a system from matrix that establishes the relations among them (Villacorta et al., 2012). In this study, the identification and classification of supply chain performance indices is essentially required for the implementation of an efficient g-resilient index evaluation system. The objective of MICMAC analysis is to analyze and classify the performance indicators based on their driving power and dependence. Based on the concept of MICMAC, g-resilient performance criteria have been classified into four clusters according to their driving power and dependence value.

**Step 7: Development of an ISM Model**

After level partitioning, lower triangular form of reachability matrix is prepared by arranging the elements according to their levels. After removing the indirect links, a digraph is drawn by means of nodes or vertices and lines of edges. The relationship between elements *i* and *j* is shown by an arrow which connects from *i* to *j*. This constructed digraph is then converted into an ISM based model by mentioning the descriptions of elements within it. The elements of ISM model is connected in a complete hierarchical form.

## 6.4 Proposed Decision Support Framework

***Step 1***. Identification of green and resiliency criteria (performance indices) in relation to the case company (i.e. supply chain in which the company operates).

***Step 2***. Selection of a decision making group /expert team in order to collect expert judgment on priority weight as well as appropriateness rating (performance extent) of various criteria (as identified in Step 1) in the form of natural language representation (subjective human thought).

***Step 3***. Selection of a suitable fuzzy scale, enriched with trapezoidal fuzzy numbers set theory, to transform subjective information (as provided by the Decision-Makers; obtained in Step 2) into appropriate fuzzy values.

***Step 4***. Aggregation of the preferences of multi-judge to compute aggregated fuzzy weight and aggregated fuzzy rating against individual criterion by the application of fuzzy aggregation rule.

Assuming that, a decision making group consists of $K$ Decision-Makers; then the weight and rating of individual supply chain practices (criterion) can be calculated as:

$$\tilde{w}_j = \frac{1}{K}\left[\tilde{w}_j^1 \oplus \tilde{w}_j^2 \oplus \ldots \oplus \tilde{w}_j^k \oplus \ldots \oplus \tilde{w}_j^K\right] \tag{6.8}$$

$$\tilde{U}_j = \frac{1}{K}\left[\tilde{U}_j^1 \oplus \tilde{U}_j^2 \oplus \ldots \oplus \tilde{U}_j^k \oplus \ldots \oplus \tilde{U}_j^K\right] \tag{6.9}$$

where, $j = G_1 \ldots\ldots, G_7$ (Green practices/criteria) and

$j = R_1 \ldots\ldots, R_7$ (Resiliency criteria)

Here $\tilde{w}_j^k$ and $\tilde{U}_j^k$ are the rating and the importance weight of the criterion $G_j$ (or $R_j$) as given by the $K^{th}$ decision-maker.

***Step 5***. Calculation of supply chain's ecosilient (g-resilient) index.

The performance extent ($\tilde{U}_G$) considering individual green supply chain practices $(G_1, \ldots, G_7)$ can be calculated as follows.

$$\tilde{U}_G = \frac{\sum_{j=G_1}^{G_7} \tilde{U}_j \otimes \tilde{w}_j}{\sum_{j=G_1}^{G_7} \tilde{w}_j} \tag{6.10}$$

The performance extent ($\tilde{U}_R$) considering individual resilient supply chain practices $(R_1,...,R_7)$ can be calculated as follows.

$$\tilde{U}_R = \frac{\sum_{j=R_1}^{R_7} \tilde{U}_j \otimes \tilde{w}_j}{\sum_{i=R_1}^{R_7} \tilde{w}_j} \tag{6.11}$$

Now, ecosilient/ g-resilient index $(GRI)$ of the supply chain can be computed as follows:

$$GRI\Big|_{Fuzzy} = \frac{\tilde{U}_G + \tilde{U}_R}{2} \tag{6.12}$$

(Assuming equal importance for both green as well as resiliency properties/practices)

***Step VI***. In this step the calculation of 'Fuzzy Performance Importance Index' (FPPI) against individual criterion, according to (Eq. 13), is shown below.

$$FPII_j = \left[\{(1,1,1,1) - \tilde{w}_j\} \otimes \tilde{U}_j\right] \tag{6.13}$$

The concept of FPII was introduced by (Lin et al., 2006) for agility evaluation in industrial supply chain. If $\tilde{w}_j$ would have been used directly to calculate the $FPII_j$; the importance weights $\tilde{w}_j$ could neutralize performance ratings in calculating $FPII_j$; in this case, it would have become impossible to identify the actual main obstacles/i.e. poor performing areas (low performance rating and high importance). If $\tilde{w}_j$ is high, then the transformation $\left[(1,1,1,1) - \tilde{w}_j\right]$ is low. Consequently, to elicit a factor with low performance rating and high importance, for each criteria considered herein, the $FPII_j$, indicating the effect of each supply chain performance criterion have such been defined. The $FPII_j$ combines the performance rating and the importance weight of each criterion.

In this work, the concept of $FPII_j$ has been used to identify ill (poor)-performing areas (criteria) which should perform better towards future improvement of supply chain's ecosilient (g-resilient) performance.

***Step 7***. Ranking and categorization of various criteria are carried out in this step in accordance with their performance.

Considering an Ideal Fuzzy Performance Index i.e. $FPII_j$ as $(1,1,1,1)$; this is so because performance index is said to be ideal if it is close to 1. The FPIIs of individual criterion is compared with the 'ideal FPII' chosen, to estimate Degree of Similarity (DOS) (as discussed in **Section 6.3.1; Definition 3**). DOS helps to understand about the performance behavior of various performance indicators.

Since FPII being a fuzzy number, it seems difficult of rank different criteria. Hence, it is felt that a comparison scheme has to be explored so as to obtain a 'representative crisp' value against each performance indicator. DOS value being a crisp number, it facilitates in deriving ranking order of various criteria.

Similarity measure between two fuzzy numbers is related to their commonality, in theories of the recognition, identification, and categorization of objects, where a common assumption is that the greater the commonality (close to 1) between a pair of objects, more similar they are (Guha, and Chakrabort, 2010).

Here, $\tilde{A} = FPII_j = \left[\{(1,1,1,1) - \tilde{w}_j\} \otimes \tilde{U}_j\right]$ i.e. Fuzzy Performance Importance Index (FPII) and, $\tilde{B} = Ideal\ FPPI = (1,1,1,1)$ i.e. Ideal Fuzzy Performance Importance Index (IFPPI)

Finally, supply chain performance criteria are ranked according to their Degree of Similarity (DOS) values arranged in descending order. The criterion, whose FPII exhibits higher degree of similarity as compared with 'ideal FPII'; is said to be the one contributing more towards g-resilient performance index in relation to the company's supply chain. Moreover, supply chain performance indicators are categorized into three distinct levels (viz. regretful, tolerable and satisfactory) based on the Degree of Similarity $S(\tilde{A}, \tilde{B})$ values. By exploring the concept of Degree of Similarity (DOS) delineated in the trapezoidal fuzzy numbers set theory, difference supply chain performance indicators are ranked and thus categorized into various performance levels. By this way, ill-poor (regretful) performing areas (criteria) can be identified.

***Step 8***. Establishing interrelationships amongst various supply chain g-resilient performance criteria through exploration of Interpretive Structural Modeling (ISM).

## 6.5 Case Empirical Study

The case automotive company considered herein located at the southern part of India. In this study, the supply chain g-resilient performance index of the considered case automotive company has been determined by considering the green as well as the resiliency criteria both.

### 6.5.1 Evaluation of G-Resilient Performance Index

Six Decision-Makers (DMs) have been carefully selected from the top managerial level of the case automotive company based on their profile and working experience. A set of fourteen supply chain practices (performance criteria) have been considered as a combination of green and resilient strategy (as shown in Table 6.1). Definition of green supply chain practices and resilient supply chain practices have also been given in Table 6.2 and Table 6.3, respectively. Two different scales consisting of 9-member linguistic terms (as shown in Table 6.4) have been selected for the assignment of priority weight as well as rating of performance criteria. The expert team members have been requested to provide their response (personal judgment) in regards of subjective weight as well as rating against each of the performance indicators (criteria) with the linguistic variables prescribed in Table 6.4. A questionnaire based survey has been conducted (refer to APPENDIX A). Linguistic data as collected from the decision making group have been furnished in Table 6.5 and Table 6.6, respectively. These have further been transformed into appropriate fuzzy representations as indicated in Table 6.4. Using aggregation rule in fuzzy set theory, Decision-Makers' pulled opinion has been obtained in terms of aggregated fuzzy weight as well as aggregated fuzzy rating against individual criterion [Refer to **Section 6.4**; *Step 4;* Eq. (6.8-6.9)]; results have been shown in Table 6.5 and Table 6.6, respectively. Using Eq. (6.10-6.11), the green and resiliency performance extent of the supply chain has been computed separately and shown in Table 6.7. Next, Ecosilient (g-resilient) index has been calculated using Eq. (6.12) as shown in Table 6.7 (Refer to **Section 6.4**; *Step 6*). In later stage, the Fuzzy Performance Importance Index (FPPI) has been calculated (using data from Table 6.5 and Table 6.6) for each of the performance indicators using Eq. (6.13); results have been shown in Table 6.8 (Refer to **Section 6.4** *Step 7).*

The Degree of Similarity (DOS), $S(\tilde{A},\tilde{B})$ against each supply chain performance indicator (Green+ Resilient) has been computed (Refer to **Section 6.4;** *Step 7)* using Eq. (6.7) and shown in Table 6.8 and Fig. 6.3. After that, the various supply chain performance indicators have been ranked (Table 6.8) according to their DOS values arranged in descending order. Considering a predefined range [0, 1], supply chain performance indicators have been categorized according to their DOS values into three distinct levels such as **REGRETFUL** (Range~0.494-0.506), **TOLERABLE** (Range~0.506- 0.515) and **SATISFACTORY** (Range~0.515- 0.546). Thus, all fourteen supply chain practices (criteria) have been arranged into their appropriate performance level as shown in Table 6.9 (Refer to **Section 6.4**; *Step 7*).

Total fourteen supply chain practices (combination green and resilient criteria) have been considered for this study in order to find the unique g-resilient index for the case automotive company. The g-resilient index (crisp) of case company has been obtained as $GRI$ =0.646. From Table 6.8, it has been inferred that the supply chain performance indicator i.e. $R_7$ (Developing visibility to a clear view of downstream inventories and demand conditions) has appeared as the highest performing criterion, followed by $G_7$ (Reverse logistic). While, $G_3$ (ISO 14001 certification) and $R_6$ (Flexible transportation) have to be undergone considerable improvements for this particular case company. Graphical representation indicating a comparison on the performance extent of various performance criteria (according to their DOS values) has been provided in Fig. 6.3. In addition to that, performance criteria viz. $G_1$, $G_3$, $R_4$, $R_6$ have been reported possessing poor performance; and thus requiring future improvements. $G_4$, $G_5$, $R_2$, $R_3$, $R_5$ etc. have been found exhibiting satisfactory performance. However, few supply chain criteria (viz. $G_2$, $G_6$, $G_7$, $R_1$, $R_7$ etc.) have been found excellent in their performance.

The main purpose of conducting this study has been to derive a unique quantitate index representing supply chain’s ecosilient (g-resilient) performance to encourage company managers towards implementation of the proposed index system. Moreover, such g-resilient index evaluation framework can be useful for the managers of the automotive sector in order to reduce the environmental ill-impacts and to improve the ability of the organization to cope up with unexpected disturbances.

### 6.5.2 Interrelationships Amongst Performance Indicators: Results of ISM Modeling

In later stage, supply chain performance indicators (viz. $G_1$, $G_2$, $G_3$, $G_4$, $G_5$, $G_6$, $G_7$, $R_1$, $R_2$, $R_3$, $R_4$, $R_5$, $R_6$, $R_7$) have been considered again for the analysis through ISM. Following the procedural steps as prescribed in ISM literature, Structural Self-Interaction Matrix (SSIM) has been developed and shown in Table 6.10. Final reachability matrix (as shown in Table 6.11) has thus been obtained. Level partitioning of aforementioned supply chain performance indicators has now been achieved; and, the summary of level partitioning has been shown in Table 6.12.

Then, MICMAC analysis has been performed; supply chain performance indicators have been placed into their appropriate quadrants (refer to Fig. 6.4) viz. autonomous (Cluster I), dependent (Cluster II), linkage (Cluster III) and driver (Cluster IV). Autonomous is a factor which have weak driving power and weak dependence power. It has been found that four performance indices coming under autonomous cluster viz. $G_1$, $G_5$, $G_6$ and $R_1$. Dependent is the factor which have weak driving power and strong dependence power. The following performance indicators viz. $G_2$, $G_3$, $G_4$ and $R_3$ have been found reported to be under this quadrant. Linkage factors should have both, strong driving and dependence power; none of the supply chain performance indicator has appeared in this cluster. Driver cluster factors should correspond to strong driving power but weak dependence power. The following performance indicators viz. $G_7$, $R_2$, $R_4$, $R_5$, $R_6$ and $R_7$ have been found under this quadrant. Further, the ISM has been used to establish the relationship amongst various performance indicators of the g-resilient supply chain; a relationship diagram (ISM model) has been developed (in hierarchical form) and shown in Fig. 6.5. Thus, the developed ISM model has segregated performance indicators into a hierarchy of nine different levels as presented in (Fig. 6.5).

## 6.6 Discussion

The present research has been planned as an extension of the earlier work as reported by (Azevedo et al., 2013b); in which the authors used fourteen criteria/performance indicators (combination of green and resilient supply chain practices) to determine the g-resilient index in order to assess greenness and resilience of an automotive supply chain for four care companies. In doing so, (Azevedo et al., 2013b) developed an integrated assessment model based on green and resilient supply chain practices/ paradigm (as shown in Fig. 6.2).

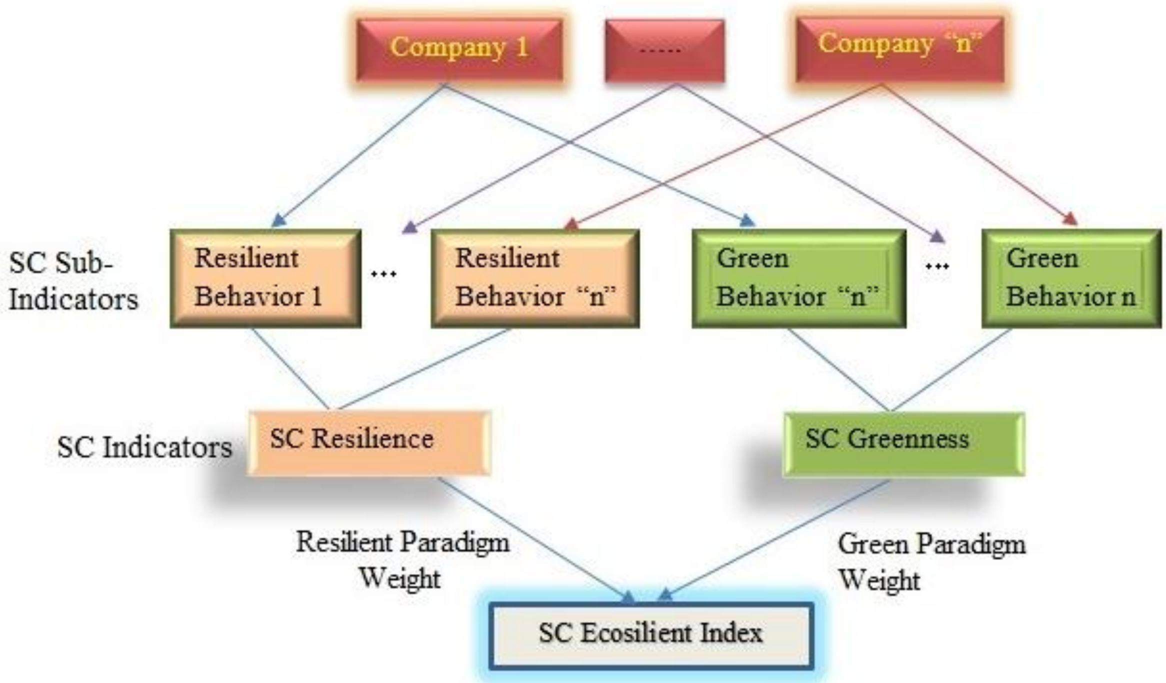


Fig. 6.2: Hierarchical relationships involved in assessment of g-resilient index

Green SC practices and Resilient SC practices were assessed on the basis of a five point Likert scale where 1 means 'practice not implemented' and 5 represents 'practice totally implemented' through a questionnaire based (Delphi round) survey. The Delphi technique was used to weight various supply chain practices according to their importance. The authors further, stated that the ecosilient index is a composite indicator which is a function of the Supply Chain (SC) practice (Green+ Resilient) and their corresponding priority weights. The ecosilient index (crisp) for the four case companies was then calculated.

In the work by (Azevedo et al., 2013b), four case companies' g-resilient culture was combined to determine a unique ecosilient performance index for the supply chain. On the contrary, the present study has attempted to evaluate g-resilient index for a single case company (and corresponding supply chain on which the company has been operating). Additionally, this study has been enriched with the application of Interpretive Structural Modeling (ISM) in order to discover the interrelationship amongst various green as well as resilient supply chain practices/performance indicators.

## 6.7 Concluding Remarks

An integrated decision support framework has been suggested in this work to determine a unique index known as 'Ecosilient (G-Resilient) index' towards exploring 'greenness' as well as 'resiliency' in supply chain for the case automotive company, simultaneously. Application potential of the proposed ecosilient (g-resilient) index evaluation system has been elaborated through a case empirical study. By following this framework, environmental impacts can be reduced; company can cope up with unexpected disturbances and disruptions. The proposed framework may be used to identify poor (ill) performing supply chain performance criteria which require future improvement. The unique g-resilient index may be helpful in comparing performance of different companies operating under similar supply chain construct. In doing so, benchmark g-resilient practices can easily be identified. Organizations can follow those practices in order to boost up overall g-resilient performance of the supply chain.

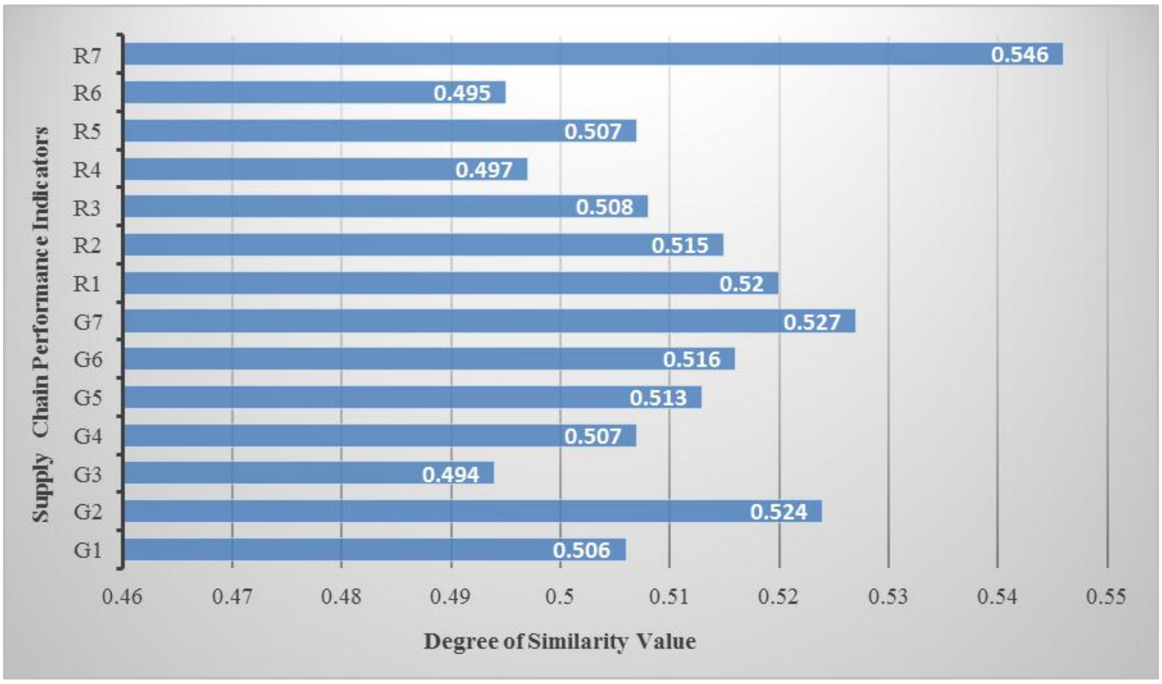


Fig. 6.3: Performance extent of various g-resilient indices (performance criteria)

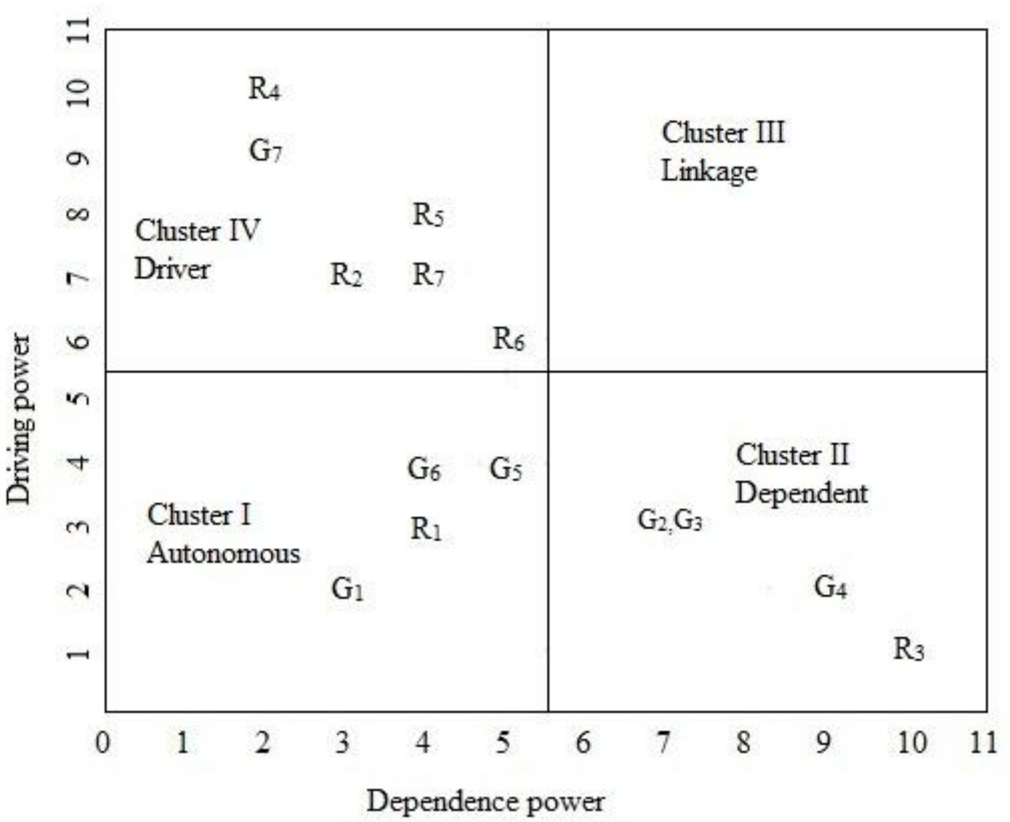


Fig. 6.4: Driver power and dependence power matrix

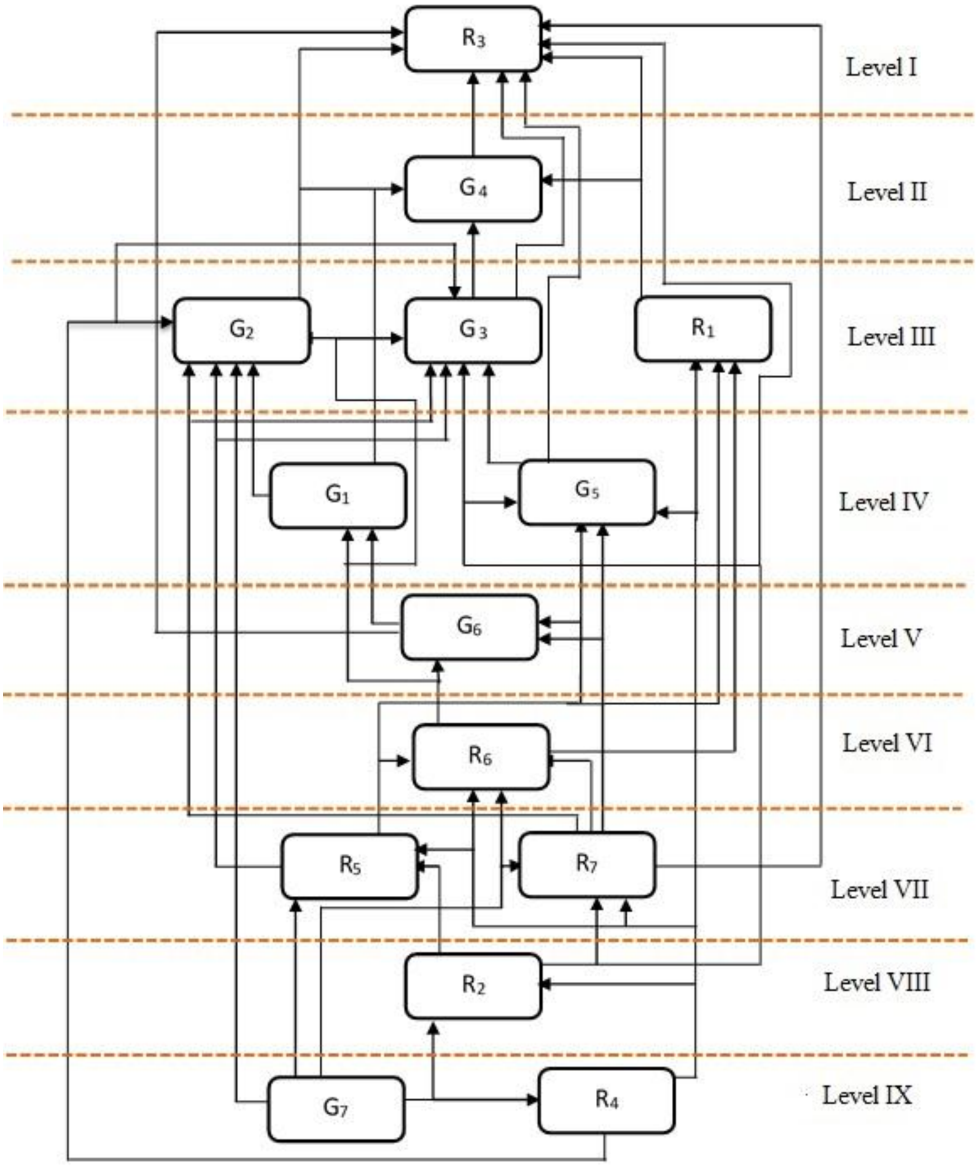


Fig. 6.5: Interpretive Structural Model (ISM) exhibiting interrelationships amongst various g-resilient performance indicators

Table 6.1: Supply chain g-resilient performance evaluation index system

| Nature of supply chain practices (NSCP) /Supply chain paradigm | Notation | Supply chain practices (SCP)/performance indices/criteria |
|---|---|---|
| Green | $G_1$ | Environmental collaboration with suppliers |
| | $G_2$ | Environmental monitoring upon suppliers |
| | $G_3$ | ISO 14001 certification |
| | $G_4$ | To reduce energy consumption |
| | $G_5$ | To reuse/recycling materials and packaging |
| | $G_6$ | Environmental collaboration with the customer |
| | $G_7$ | Reverse logistics |
| Resilient | $R_1$ | Sourcing strategies to allow switching of suppliers |
| | $R_2$ | Flexible supply base/flexible sourcing |
| | $R_3$ | Strategy stock |
| | $R_4$ | Lead time reduction |
| | $R_5$ | Creating total supply chain visibility |
| | $R_6$ | Flexible transportation |
| | $R_7$ | Developing visibility to a clear view of downstream inventories and demand conditions |

Table 6.2: Definition of green supply chain practices

| Green supply chain practices | Clarification |
| --- | --- |
| Environmental collaboration with suppliers | Environmental collaboration with suppliers includes a set of activities those are responsible to improve environmental performance. This collaboration is supposed to examine the suppliers' capability to work under joint projects for developing green products and innovations (Bowen et al., 2001; Hall, 2000; Rao, 2002; Vachon and Klassen, 2006a, b). It allows interaction between organizations and suppliers related to the joint environmental planning or program which may include technological and organizational development of projects (Sarkis 2003, Vachon and Klassen 2008). Association of organization with suppliers is important to achieve environmental goals collectively, developing a mutual understanding of responsibilities regarding environmental performance and conducting joint planning to anticipate and resolve environmental-related problems (Grekova et al., 2016). |
| Environmental monitoring upon suppliers | It includes continuous auditing and monitoring of suppliers' performance to infer whether the green supplier development programs are effectively contributing to the performance or not (Bai and Sarkis, 2010b). The environmental monitoring actually emphases on the outcome of environment-related practices made by the suppliers in terms of achieving certification (e.g. ISO 14001 or Eco-management and audit scheme well known as EMAS) being in compliance with other regulations (e.g. emissions caps or hazardous material labeling), or having the environment-related documentation in order (Krut and Karasin, 1999). Environmental monitoring comprises activities of collecting and handling supplier information through publicly disclosed environmental records, company-specific surveys, and audits accompanied by either the buyer or an independent third party (Min and Galle, 2001). |
| ISO 14001 certification | ISO 14001 environmental management systems (EMS) is an organized and procedure driven tactic in order to deal with those facets of any business, having the substantial impact on the environment. The EMS is developed to make business owners and managers aware of their environmental responsibilities, including legal and regulatory liabilities, and capable enough to manage and control associated risks. Adherence to ISO 14001 can provide assurance to company management and workers as well as external stakeholders that environmental impact is being measured and improved (Source: http://www.iso.org/iso/iso14000). It describes the criteria for an environmental management system requiring commitment to compliance with appropriate legislation, regulation and continuous development (Nishitani, 2010). |

Table 6.2 (continued): Definition of green supply chain practices

| Green supply chain practices | Clarification |
|---|---|
| To reduce energy consumption | Excess energy consumption is one of the prime reasons for the global warming causing adverse environmental effects thus affecting social and economic platform. Reduction in the energy consumption by using the available resources in an environment-friendly manner seems the appropriate ways to mitigate environmental harms. It consists of improving environmental performance throughout the supply chain with more efficient processes thereby reducing energy consumption (Tate et al., 2011) |
| To reuse/recycling materials and packaging | This involves effective reuse and recycling of the product so that the amount of solid waste disposal can be reduced (Humphreys et al., 2003). The product design must include possible means to reuse, recycle and recovery of the material (Hsu et al., 2012). The extent of use and reuse of packages necessitates cooperation with suppliers that helps to decrease storage and recovery delays; thus ensures operational cost savings and at the same time being environmentally correct (Rao and Holt, 2005). |
| Environmental collaboration with the customer | Environmental collaboration with the customer includes activities having a clear intention to improve environmental performance and proficiencies of customer at undertaking joint projects for developing green products and innovations (Vachon and Klassen, 2006a, b). In this context, suppliers and customers should plan together regarding the reduction of environmental impact caused during production processes. Environmental collaboration includes sharing of technical information and needs a mutual willingness to know about each other's operations to plan and define objectives for environmental improvement. It also implies cooperation to diminish the environmental influence related to the flow of materials through the supply chain network (Bowen et al., 2001; Carter and Carter, 1998). |
| Reverse logistics | Reverse logistic is all about the management of the flow of the products or the parts intended for remanufacturing, recycling and disposal by effectively use of resources (Dowlatshahi, 2000). It includes all the activities linked with the collection and either recovery or disposal of previously used products (Ilgin and Gupta, 2010) |

Table 6.3: Definition of resilient supply chain practices

| Resilient supply chain practices | Clarification |
|---|---|
| Sourcing strategies to allow switching of suppliers | It represents a strategic policy which enables organization to switch over the alternative supplier in minimum time, if needed. This also describes as the ability of an organization to switch over different suppliers quickly to develop a recovery when compared to a less dense network (Greening and Rutherford, 2011). |
| Flexible supply base/flexible sourcing | Flexible supply base enables a firm to handle regular demand fluctuations; it can also be used to maintain continuous supply of materials, when a major disruption occurs. It ensures the accessibility of a range of options and the availability of the purchasing process to effectively exploit them so as to respond to changing recruitments related to the supply of obtained components (Swafford et al., 2006; Tachizawa and Thomsen 2007). |
| Strategy stock | Strategy stock increases the product availability within the firm which improves capability to manage the supply and demand, if raised suddenly. It also allows a firm to respond to market demand quickly during a major disturbance. It consists of holding some inventories at certain "strategic" locations (Warehouse, Logistics hubs, Distribution Centers) to be shared by multiple supply chain partners (retailers, repair centers etc.) (Tang, 2006). |
| Lead time reduction | To increase the performance of supply chain, it is always better to focus first on lead time reduction, resulting in positive demand chain improvement (de Treville et al., 2004). When the lead time is long, a supply chain becomes more vulnerable to disruption. To decrease the impact of risk, lead time can be reduced by reshaping the supply chain network (Tang, 2006) |
| Creating total supply chain visibility | Increasing supply chain visibility is a critical strategy for the enterprises aiming at reducing cost and improving operational performance in the context of their complex and multi-tired global supply demand network. A clear picture of inventories and flows in the supply chain, status of vendors, manufacturers, intermediates and customers and the logistics network seems to be the foremost necessity for effective supply chain management (Lakovou et al., 2007). |

Table 6.3 (continued): Definition of resilient supply chain practices

| Resilient supply chain practices | Clarification |
| --- | --- |
| Flexible transportation | This practice includes multi-model transportation, multi-carrier transportation and multiple routes to ensure a nonstop (smooth) flow of materials even when transportation distributions occurs (Tang, 2006). |
| Co-ordination with downstream partners | Co-ordination with downstream partners is indeed mandatory to cope up with demand in a beneficial manner.<br>Supply chain partners should who exchange information regularly on downstream inventories and demand conditions that can anticipate market trends and demand risk (Christopher and Peck, 2004); thereby, ensuring response to disruption becoming more quickly by rerouting shipments, adjusting capacities and/or revising the original production plans (Lakovou et al., 2007). |

Table 6.4: Linguistic scales (and corresponding fuzzy representation) for assigning priority weight and rating against individual criteria

| Linguistic terms (Priority weight) | Linguistic terms (Attribute/criteria rating) | Generalized trapezoidal fuzzy numbers |
| --- | --- | --- |
| Absolutely Low (AL) | Absolutely Poor (AP) | (0,0,0,0;1.0) |
| Very Low (VL) | Very Poor (VP) | (0,0,0.02,0.07;1.0) |
| Low (L) | Poor (P) | (0.04,0.1,0.18,0.23;1.0) |
| Medium Low (ML) | Medium Poor (MP) | (0.17,0.22,0.36,0.42;1) |
| Medium (M) | Medium (M) | (0.32,0.41,0.58,0.65;1.0) |
| Medium High (MH) | Medium Good (MG) | (0.58,0.63,0.80,0.86;1.0) |
| High (H) | Good (G) | (0.72,0.78,0.92,0.97;1.0) |
| Very High (VH) | Very Good (VG) | (0.93,0.98,1.0,1.0;1.0) |
| Absolutely High (AH) | Absolutely Good (AG) | (1.0,1.0,1.0,1.0;1.0) |

Table 6.5: Decision makers' subjective response (corresponding aggregated fuzzy weight) for green and resilient supply chain practices

| NSCP | Supply chain practices (SCP) | DM1 | DM2 | DM3 | DM4 | DM5 | DM6 | Aggregated Fuzzy Weight |
|---|---|---|---|---|---|---|---|---|
| $\tilde{w}_j$ $j = G_1, G_2, ..., G_7$ | Environmental collaboration with suppliers | MH | VH | VH | ML | M | VL | (0.488,0.537,0.627,0.667) |
| | Environmental monitoring upon suppliers | M | L | M | M | M | VL | (0.220,0.290,0.420,0.483) |
| | ISO 14001 certification | H | H | AH | ML | VH | MH | (0.687,0.732,0.833,0.870) |
| | To reduce energy consumption | H | M | H | M | M | L | (0.407,0.482,0.627,0.687) |
| | To reuse/recycling materials and packaging | M | L | AH | MH | L | AH | (0.497,0.540,0.623,0.662) |
| | Environmental collaboration with the customer | MH | L | ML | M | L | L | (0.198,0.260,0.380,0.437) |
| | Reverse logistics | H | L | M | MH | ML | L | (0.312,0.373,0.503,0.560) |
| $\tilde{w}_j$ $j = R_1, R_2, ..., R_7$ | Sourcing strategies to allow switching of suppliers | M | M | M | M | M | MH | (0.338,0.415,0.580,0.647) |
| | Flexible supply base/flexible sourcing | MH | MH | MH | H | ML | M | (0.492,0.550,0.710,0.770) |
| | Strategy stock | M | MH | AH | H | ML | H | (0.585,0.637,0.763,0.812) |
| | Lead time reduction | H | M | VH | MH | MH | AH | (0.688,0.738,0.850,0.890) |
| | Creating total supply chain visibility | VH | ML | AH | MH | M | H | (0.620,0.670,0.777,0.817) |
| | Flexible transportation | VH | L | AH | H | M | H | (0.622,0.675,0.767,0.803) |
| | Developing visibility to a clear view of downstream inventories and demand conditions | AH | ML | VL | M | M | H | (0.422,0.470,0.577,0.627) |

Table 6.6: Decision makers' subjective response (corresponding aggregated fuzzy rating) for green and resilient supply chain practices

| NSCP | Supply chain practices (SCP) | DM1 | DM2 | DM3 | DM4 | DM5 | DM6 | Aggregated Fuzzy Rating |
|---|---|---|---|---|---|---|---|---|
| $\tilde{U}_j$ $j = G_1, G_2, ..., G_7$ | Environmental collaboration with suppliers | MG | MP | VG | MP | M | VP | (0.362,0.410,0.520,0.570) |
| | Environmental monitoring upon suppliers | M | M | M | M | M | VP | (0.267,0.342,0.487,0.553) |
| | ISO 14001 certification | MG | M | AG | MP | G | MG | (0.562,0.612,0.743,0.793) |
| | To reduce energy consumption | M | MP | G | M | M | P | (0.315,0.388,0.533,0.595) |
| | To reuse/recycling materials and packaging | MG | M | AG | MG | P | P | (0.427,0.478,0.590,0.638) |
| | Environmental collaboration with the customer | M | MP | P | MG | MP | P | (0.220,0.280,0.410,0.468) |
| | Reverse logistics | G | MP | M | MG | P | M | (0.358,0.425,0.570,0.630) |
| $\tilde{U}_j$ $j = R_1, R_2, ..., R_7$ | Sourcing strategies to allow switching of suppliers | MG | P | M | M | M | MG | (0.360,0.432,0.587,0.650) |
| | Flexible supply base/flexible sourcing | VG | M | G | M | M | M | (0.488,0.567,0.707,0.762) |
| | Strategy stock | G | MG | M | MG | M | G | (0.540,0.607,0.767,0.827) |
| | Lead time reduction | MG | M | VG | MG | MG | AG | (0.665,0.713,0.830,0.872) |
| | Creating total supply chain visibility | G | G | G | M | M | G | (0.587,0.657,0.807,0.863) |
| | Flexible transportation | MG | VP | MG | M | M | G | (0.420,0.477,0.617,0.677) |
| | Developing visibility to a clear view of downstream inventories and demand conditions | VG | MP | AG | G | MP | G | (0.618,0.663,0.760,0.797) |

Table 6.7: Calculation of g-resilient performance index

<table>
<tr><th>Green Practices</th><th>$\tilde{U}_j \otimes \tilde{w}_j$<br>$j = G_1, G_2, ..., G_7$</th><th>$\tilde{U}_G$</th><th>$GRI \mid Fuzzy$</th><th>$GRI \mid Crisp$</th></tr>
<tr><td>$G_1$</td><td>(0.177,0.220,0.326,0.380)</td><td rowspan="7">(0.256,0.360,0.714,0.971)</td><td rowspan="16">(0.316,0.426,0.799,1.043)</td><td rowspan="16">0.646</td></tr>
<tr><td>$G_2$</td><td>(0.059,0.099,0.204,0.267)</td></tr>
<tr><td>$G_3$</td><td>(0.386,0.448,0.619,0.690)</td></tr>
<tr><td>$G_4$</td><td>(0.128,0.187,0.334,0.409)</td></tr>
<tr><td>$G_5$</td><td>(0.212,0.258,0.368,0.422)</td></tr>
<tr><td>$G_6$</td><td>(0.044,0.073,0.156,0.205)</td></tr>
<tr><td>$G_7$</td><td>(0.112,0.159,0.287,0.353)</td></tr>
<tr><td>Resiliency Practices</td><td>$\tilde{U}_j \otimes \tilde{w}_j$<br>$j = R_1, R_2, ..., R_7$</td><td>$\tilde{U}_R$</td></tr>
<tr><td>$R_1$</td><td>(0.122,0.179,0.340,0.420)</td><td rowspan="7">(0.377,0.493,0.883,1.115)</td></tr>
<tr><td>$R_2$</td><td>(0.240,0.312,0.502,0.586)</td></tr>
<tr><td>$R_3$</td><td>(0.316,0.386,0.585,0.671)</td></tr>
<tr><td>$R_4$</td><td>(0.458,0.527,0.706,0.776)</td></tr>
<tr><td>$R_5$</td><td>(0.364,0.440,0.627,0.705)</td></tr>
<tr><td>$R_6$</td><td>(0.261,0.322,0.473,0.544)</td></tr>
<tr><td>$R_7$</td><td>(0.261,0.312,0.438,0.499)</td></tr>
</table>

Table 6.8: DOS between $\tilde{A} = (1 - \tilde{w}_j) \otimes \tilde{U}_j$ and $\tilde{B} = Ideal\ FPII$ : Ranking order of supply chain performance indicators

| SCM Practice | $\tilde{A} = (1 - \tilde{w}) \otimes \tilde{U}$ | $\tilde{B}$ = Ideal FPII | $S(\tilde{A}, \tilde{B})$ | Ranking order |
|---|---|---|---|---|
| $G_1$ | (0.185,0.190,0.194,0.190) | (1,1,1,1) | 0.506 | 11 |
| $G_2$ | (0.208,0.243,0.282,0.286) | | 0.524 | 3 |
| $G_3$ | (0.176,0.164,0.124,0.103) | | 0.494 | 14 |
| $G_4$ | (0.187,0.201,0.199,0.186) | | 0.507 | 10 |
| $G_5$ | (0.215,0.220,0.222,0.216) | | 0.513 | 7 |
| $G_6$ | (0.176,0.207,0.254,0.264) | | 0.516 | 5 |
| G7 | (0.247,0.266,0.283,0.277) | | 0.527 | 2 |
| $R_1$ | (0.238,0.253,0.246,0.230) | | 0.520 | 4 |
| $R_2$ | (0.248,0.255,0.205,0.175) | | 0.515 | 6 |
| $R_3$ | (0.224,0.220,0.181,0.156) | | 0.508 | 8 |
| $R_4$ | (0.207,0.187,0.125,0.096) | | 0.497 | 12 |
| $R_5$ | (0.223,0.217,0.180,0.158) | | 0.507 | 9 |
| $R_6$ | (0.159,0.155,0.144,0.133) | | 0.495 | 13 |
| $R_7$ | (0.358,0.352,0.322,0.297) | | 0.546 | 1 |

Table 6.9: Categorization of supply chain performance indicators into three distinct levels

| Category | Range | Supply chain practices |
|---|---|---|
| Regretful | 0.494-0.506 | $G_1$, $G_3$, $R_4$, $R_6$ |
| Tolerable | 0.506-0.515 | $G_4$, $G_5$, $R_2$, $R_3$, $R_5$ |
| Satisfactory | 0.515-0.546 | $G_2$, $G_6$, $G_7$,$R_1$,$R_7$ |

Table 6.10: Structural self-interaction matrix (SSIM)

| SC performance indicators | $R_7$ | $R_6$ | $R_5$ | $R_4$ | $R_3$ | $R_2$ | $R_1$ | $G_7$ | $G_6$ | $G_5$ | $G_4$ | $G_3$ | $G_2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $G_1$ | O | A | O | O | O | O | O | O | A | O | O | O | V |
| $G_2$ | A | A | A | A | V | O | O | A | O | O | V | O | |
| $G_3$ | A | A | A | A | V | A | O | O | O | A | O | | |
| $G_4$ | O | O | A | O | V | A | A | A | A | A | | | |
| $G_5$ | A | O | A | A | V | A | O | O | O | | | | |
| $G_6$ | A | A | A | O | V | O | O | O | | | | | |
| $G_7$ | V | V | V | X | V | V | O | | | | | | |
| $R_1$ | O | A | A | A | V | O | | | | | | | |
| $R_2$ | V | O | V | A | V | | | | | | | | |
| $R_3$ | A | O | O | O | | | | | | | | | |
| $R_4$ | V | V | V | | | | | | | | | | |
| $R_5$ | O | V | | | | | | | | | | | |
| $R_6$ | A | | | | | | | | | | | | |

Table 6.11: Final reachability matrix with driving and dependence power

| SC performance indicators | $G_1$ | $G_2$ | $G_3$ | $G_4$ | $G_5$ | $G_6$ | $G_7$ | $R_1$ | $R_2$ | $R_3$ | $R_4$ | $R_5$ | $R_6$ | $R_7$ | Driving |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $G_1$ | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| $G_2$ | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 3 |
| $G_3$ | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 3 |
| $G_4$ | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 2 |
| $G_5$ | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 4 |
| $G_6$ | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 4 |
| $G_7$ | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 9 |
| $R_1$ | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 3 |
| $R_2$ | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 7 |
| $R_3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |
| $R_4$ | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 10 |
| $R_5$ | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 8 |
| $R_6$ | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 6 |
| $R_7$ | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 7 |
| Dependence | 3 | 7 | 7 | 9 | 5 | 4 | 2 | 4 | 3 | 10 | 2 | 4 | 5 | 4 | 69/69 |

Table 6.12: Summary of level partitioning

| SC performance indicators | Reachability set | Antecedent set | Intersection set | Level |
|---|---|---|---|---|
| $G_1$ | $G_1$,$G_2$ | $G_1$,$G_6$,$R_6$ | $G_1$ | IV |
| $G_2$ | $G_2$,$G_4$,$R_3$ | $G_1$,$G_2$,$G_7$,$R_4$,$R_5$,$R_6$,$R_7$ | $G_2$ | III |
| $G_3$ | $G_3$,$G_4$,$R_3$ | $G_3$,$G_5$,$R_2$,$R_4$,$R_5$,$R_6$,$R_7$ | $G_3$ | III |
| $G_4$ | $G_4$,$R_3$ | $G_2$,$G_3$,$G_4$,$G_5$,$G_6$,$G_7$,$R_1$,$R_2$,$R_5$ | $G_4$ | II |
| $G_5$ | $G_3$,$G_4$,$G_5$,$R_3$ | $G_5$,$R_2$,$R_4$,$R_5$,$R_7$ | $G_5$ | IV |
| $G_6$ | $G_1$,$G_4$,$G_6$,$R_3$ | $G_6$,$R_5$,$R_6$,$R_7$ | $G_6$ | V |
| $G_7$ | $G_2$,$G_4$,$G_7$,$R_2$,$R_3$,$R_4$,$R_5$,$R_6$,$R_7$ | $G_7$ | $G_7$ | IX |
| $R_1$ | $G_4$,$R_1$,$R_3$ | $R_1$,$R_4$,$R_5$,$R_6$ | $R_1$ | III |
| $R_2$ | $G_3$,$G_4$,$G_5$,$R_2$,$R_3$,$R_5$,$R_7$ | $G_7$,$R_2$,$R_4$ | $R_2$ | VIII |
| $R_3$ | $R_3$ | $G_2$,$G_3$,$G_4$,$G_5$,$G_6$,$G_7$,$R_1$,$R_2$,$R_3$,$R_7$ | $R_3$ | I |
| $R_4$ | $G_2$,$G_3$,$G_5$,$R_1$,$R_2$,$R_4$,$R_5$,$R_6$,$R_7$ | $G_7$,$R_4$ | $R_4$ | IX |
| $R_5$ | $G_2$,$G_3$,$G_4$,$G_5$,$G_6$,$R_1$,$R_5$,$R_6$ | $G_7$,$R_2$,$R_4$,$R_5$ | $R_5$ | VII |
| $R_6$ | $G_1$,$G_2$,$G_3$,$G_6$,$R_1$,$R_6$ | G7,$R_4$,$R_5$,$R_6$,$R_7$ | $R_6$ | VI |
| $R_7$ | $G_2$,$G_3$,$G_5$,$G_6$,$R_3$,$R_6$,$R_7$ | $G_7$,$R_2$,$R_4$,$R_7$ | $R_7$ | VII |

## Chapter 7

# E-Commerce Risk Assessment: A Fuzzy Decision Making Perspective

## 7.1 Coverage

E-commerce (EC) is primarily focused with non face-to-face communication and transactions by the application of internet resources. E-commerce provides faster buying or selling guidelines with better quality of services in a low operational cost and its territory can cover up to maximum number of customers without any geographic limitations. Due to rapid technological development; recently, online fraud as well as data hijacking are being experienced as major risks towards e-commerce development. Hence, e-commerce risk management has become an important research avenue in recent management literature.

EC risks must be controlled by adopting necessary measures in order to mitigate severity of risks. Risk is a probability or threat of damage, loss or any other negative occurrence caused by external or internal vulnerabilities. In the present context, security (data safety) of e-commerce transactions has become the primary concern for the organizations operating in internet based platform. This work focuses on development of an efficient e-commerce risk assessment framework in relation to an Indian case company, as a case empirical study. Total forty-eight risk sources have been identified in order to measure overall risk extent associated in company's e-commerce practices. The risk extent (corresponding to a particular risk source) has been measured in terms of (a) the likelihood of occurrence and (b) the impact (or consequence when such undesirable incident takes place). Due to the unavailability of quantitative historical data, aforesaid two risk quantifying parameters have been assessed through expert opinion acquired from a group of Decision-Makers (DMs) which is expressed in terms of natural language representation (subjective preferences). In later stage, subjective judgment of the DMs have been analyzed through exploration of Fuzzy Set Theory (FST). The essence of FST is that it is capable of dealing with ambiguous subjective human thought (linguistic preferences of the DMs) against vague (ill-defined) risk quantifying parameters. Based on the 'equivalent crisp score' corresponding to fuzzy risk extent against individual risk sources, potential e-commerce risk sources have been categorized into five distinct levels (viz. negligible, minor, marginal, critical and catastrophic) to represent their degree of severity. Amongst forty eight risk sources, top five risk sources, expected to severely affect the company's e-commerce performance, have been identified as 'critical' category representing their level of impact. The overall risk extent by aggregating individual risks under 'critical' level of severity has been obtained through the application of Fuzzy Inference System (FIS). Furthermore, Interpretive Structural Modeling (ISM) has been applied to develop a structural relationship amongst aforementioned five risk sources in relation to e-commerce development of the case company. Appropriate action requirement plans have also been suggested to control or minimize those risks to avoid downfall of e-commerce success.

## 7.2 Background and Problem Statement

E-commerce is basically trading of goods and services or transferring funds or data, over an electronic system, primarily the internet. Such business transactions are performed between business-to-business, business-to-consumer, consumer-to-business or consumer-to-consumer. The benefits of e-commerce comprise its round-the-clock accessibility, the speed of access, the wide availability of goods and services for the consumer, and international reach [Source: *http://searchcio.techtarget.com*]. E-commerce is mainly related to the transaction done using the internet services only whereas, E-business (EB) is the process of conducting the business over the internet, intranet or extranet. However, in broad term, both are the subsets of each other [Source: *http://www.conceptsimplified.com*]. More specifically, e-commerce includes only monetary transaction and is limited to the buying and selling only; while, e-business includes diverse activities like inventory management, production, product development, customer education, risk management etc. Nowadays, internet based transaction for trading, distributing, buying and selling products between two bodies has become a vital commercial platform to ensure fast delivery and flexibility (easiness) in operation; but, increased rate of cybercrime (like phishing, hijacking, consignment loss, data loss etc.) are the serious drawbacks of this development. Hence, understanding of e-commerce risks and associated control measures have become an important research agenda today. With the rapid development of network applications, e-commerce has already gained immense popularity; but non-face-to-face interaction between the buyer and seller, advance online payment etc. have appeared as serious e-commerce risks (Wang et al., 2008; Ting et al., 2014). Risk is as a two-dimensional perception including the possibility of an adverse consequence, and the uncertainty over the occurrence i.e. impact (Bennett et al., 1996). The primary concern of e-commerce is to ensure full privacy as well as data security with peril free operation; the same can be attained through proper understanding of various e-commerce risks with appropriate control measures towards risk mitigation.

Risk analysis is the process of defining and analyzing the dangers to individuals, businesses and government agencies, posed by natural and human-caused adverse events. Risk analysis may deal with ambiguous circumstances due to lack of exact and precise information about the state of the system (Gürcanli and Müngen, 2009). The task of risk analysis are of three types: quantitative, qualitative and semi-quantitative (Radu 2009). Quantitative techniques contain complex statistical approaches, like Monte Carlo Simulation, Fault and Event Tree Analysis, Sensitivity Analysis, Annual Loss Expectancy, Risk Exposure, Failure Mode and Effects Analysis, etc. (Rainer et al., 1991; White, 1995; Bennett et al., 1996). However, qualitative techniques rely on human judgment instead of statistical computation, for example, the scenario analysis (Zadeh, 1965, Rainer et al., 1991, Ngai and Wat, 2005).

Qualitative analysis is mostly preferable for the following circumstances: (a) where intangible aspects of risk are to be considered (i.e. reputation, culture, and image), (b) when numerical data are inadequate or unavailable, and resources are limited. On the contrary, the objective of semi-quantitative analysis is to assign some values to the scales used in the qualitative assessment. These values are basically indicative and not real; but it facilitates in adapting the quantitative approach. However, past literature depicts that most of the real-world risk analysis problems are basically the combination of quantitative and qualitative data; hence, quantitative risk assessment techniques are found insufficient for prioritizing risks associated with e-commerce. In this part of work, risk has been assessed in terms of natural language representation. Subjective human judgment basically being vague in nature; application of Fuzzy Set Theory (FST) has been found advantageous to tackle inherent uncertainty, inconsistency and imprecision in the ambiguous data set received from the group of Decision-Makers (DMs).

To this context, a fuzzy based decision support framework has been proposed herein towards effective risk assessment associated with e-commerce. The risk extent against a particular risk source (factor) has been evaluated by multiplicating two parameters: (a) likelihood (probability) of occurrence, and (b) impact (consequence) of occurrence. Finally, the identified risk sources (a total number of forty eight) have been categorized into five distinct level of severity viz. (i) Negligible, (ii) Minor, (iii) Marginal, (iv) Critical, and (v) Catastrophic.

'Negligible' level represents very low degree of severity. The risks belong to this category are insignificant and hence can be ignored. 'Minor' level encounters the risks that are incapable of imposing any noticeable effect on the performance of e-commerce execution. 'Minor' level of risks are generally the least significant and the least serious risks. 'Marginal' level includes the risks whose severity is less severe (below severe level); but, these risks should not be ignored at any stage of e-commerce practice. Risks that fall under 'critical' level are seemed dangerous and required prompt notification. When these risks come into picture, it produces alarming adverse effect on the e-commerce venture. Efforts must be made to eliminate (or reduce) critical risks on a timely manner. 'Catastrophic' level represents the topmost level of severity which includes includes risks that are prone to cause the highest dreadful effect on the e-commerce performance. Immediate actions must be taken to control the catastrophic level of risks. In this work the risk extents corresponding to individual risk sources (falling under critical level) have been aggregated by FIS to compute a unique risk extent (overall risk extent) in relation to e-commerce for the particular case company.

Finally, the interrelationship amongst critical risk sources has been developed through Interpretive Structural Modeling (ISM). Since none of the risk sources have been found which under catastrophic level of severity (for this particular case example), the ISM model has been derived only for the critical risk sources. The probability of negative occurrence that is caused by external or internal vulnerabilities in a system is well acknowledged as risk. Risk represents a situation/(condition or state) involving exposure to danger and may be avoided by incorporating appropriate preemptive action. The concept of 'risk' became popular in Economics during late 1920s. Since then, it has been successfully used in theories of decision making in economics, finance, and in decision science (Nagai and Watt, 2005).

Till now, many authors have contributed towards risk assessment in different domain to mitigate the possibility of unexpected occurrence. Karwowski and Mittal (1986) examined risks associated with the production process by the application of fuzzy set theory. The authors proposed a concept of risk evaluation using linguistic preferences of the likelihood of occurrence of a hazardous event, exposure and possible significances of that event. The approximate reasoning procedure based on fuzzy logic was used to derive fuzzy values of risk. Bonvicini et al. (1998) applied fuzzy logic to assess the risk during transportation of hazardous materials by road and pipeline in order to estimate the uncertainties affecting both individual and societal risk. Leung et al. (1998) presented an integrated Knowledge-Based System (KBS) and Bow-Tie analysis to support project managers in recognizing potential risk issues and corresponding project risks (viz. acts of god, political and environmental risks, financial and economic risks, design risks, job-site-related risks, operational and managerial risks etc.). Aqlan and Lam (2015) conducted a survey to assign the likelihoods and the impacts of supply chain risks namely, material shortage, machine failure, order cancellation, rush orders, quality problems, delay risk, innovation risk, critical customer issues, natural disasters risk, and extra inventory risk.

Organizations, executing non face-to-face and online transactions, are becoming more concerned about the issues related to e-commerce security since such transactions often encounter various risks. In order to assess e-commerce risks; past research demonstrated a variety of risk assessment models to mitigate the possibility of risk occurrence thus ensuring uninterrupted operation. Viehlandm (2001) focused on managing business risk in e-commerce and commented that risks associated with EC development are the risks of direct or indirect loss to the organization in development (involving planning, analysis, design and implementation) of an EC project. Ngai and Wat (2005) outlined a methodology for the assessment of risks associated with e-commerce development using fuzzy set theory. A Web-based prototype Fuzzy Decision Support System (FDSS) was proposed to assist e-commerce project managers in order to identify potential e-commerce risk factors. Khokhar et al. (2006) identified potential risks associated with EC projects (i.e. resources risk, requirements risk, vendor quality risk, client-server security risk, legal risk, managerial risk, outsourcing risk, physical security risk, cultural risk, re-engineering risk etc.) and proposed an extended decision support theory in combination with Dempster-Shafer (DS) method towards evaluating EC project risks. Lopez-Nicolas and Molina-Castillo (2008) evaluated the relationship between the Customer Knowledge Management (CKM) literature and e-commerce literature through several user characteristics such as risk preference, internet preference and internet knowledge and assessed their impact on the customers' online perceived risk and purchase intentions.

Bo and Congwei (2009) analyzed e-commerce security risks (viz. information tampering, data access risk, fake information, online payment risk etc.) of Chinese commercial banks and introduced a Controlled Interval and Memory (CIM) based model to quantify the risk associated therein. Ting et al. (2014) proposed a risk evaluation model based on trust to predict risk of e-commerce transactions.

Even though pioneers have attempted towards identifying and analyzing e-commerce risks; still there exists certain research gaps addressed as follows:

E-commerce risk assessment frameworks were suggested by many past researchers recommending a general risk mitigating plan. Whilst, in the present work, e-commerce risks have been classified into five distinct levels (viz. negligible, marginal, minor, critical, and catastrophic) according to their severity of adverse consequence; a set of risk mitigation plan has been separately suggested against each severity level of risks.

- Rare attempt was made to compute a quantitative index measure to represent overall risk extent in relation to a case company executing e-commerce strategy. In this study, Fuzzy Inference System (FIS) has been proposed to compute overall risk extent by aggregating extent of severity of individual risk sources that may affect company's e-commerce performance; these risks have been termed as critical. Low value of overall risk extent implies probability of high success in e-commerce.

- In-depth understanding on the interrelationship amongst various risk sources seems indeed a necessity for effective management of e-commerce risk; since these risks may be linked in such a way that mitigating one risk may provoke another risk, if these two risks are correlated. Therefore, apart from conceptualizing and formulating action requirement plans for avoiding risks, a structural relationship amongst potential e-commerce risks has also been developed herein by the application of ISM.

- Instead of assessing risk from probabilistic viewpoint, the proposed risk assessment framework has been modeled in light of decision making. The risk quantifying parameters: (a) likelihood of occurrence, and (ii) impact, both have been assessed by the opinion of multi-judge expressed in terms of linguistic terminology. To cope up with vague and ambiguous human judgment, application of fuzzy set theory and fuzzy logic has been attempted. Kou and Lu (2013) also expressed that individuals' knowledge, experience and intuitive judgment provide better assessment of risk than probabilistic approach.

To this end, the objective of the current work is to recognize the factors (risk sources) affecting e-commerce development and thereby to develop an integrated decision support framework that can effectively support qualitative risk assessment associated with e-commerce.

## 7.3 Research Methodology

The research methodology for this part of work includes fuzzy numbers set theory and Fuzzy Inference System (ISM) followed by an Interpretive Structural Modeling (ISM). Preliminaries of fuzzy numbers set theory have already been described in this dissertation and can be articulated from **Chapter 3**; **Section 3.1.1.3.3**. The Interpretive Structural Modeling (ISM) has been used to explore the interrelationship of the risks associated with e-commerce exercises in this work. ISM has also been described earlier in this dissertation and can be retrieved at **Chapter 6**; **Section 6.3.2**. [Refer: Mandal and Deshmukh, 1994; Warfield, 1994, Govindan et al., 2012; Azevedo et al., 2013a].

Fuzzy Inference System (FIS) is based on the fuzzy rule and comprises three basic units (Jamshidi et al., 2013), namely (i) Fuzzifier, (ii) Knowledge base, (iii) Inference Engine, and (iv) Defuzzifier as shown in Fig. 7.1.

The primary function of this inference system is to create a mapping from inputs to output(s). The different elements of a FIS have been described below.

**(i) Fuzzifier**

Fuzzification is the process of converting crisp values into grades of membership for linguistic terms of fuzzy sets such as Very High (VH), High (H), Medium (M), Low (L), and Very Low (VL). This process is fulfilled with the help of Membership Functions (MF). IF-THEN rules can be implemented through grades of membership for linguistic variables of fuzzy sets.

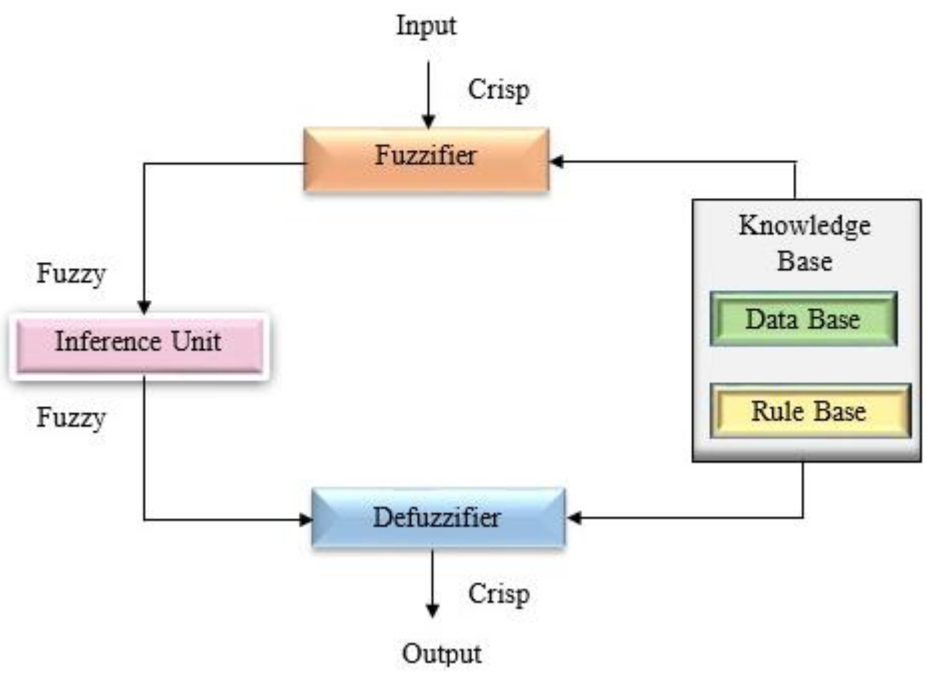


Fig. 7.1: Block diagram of Fuzzy Inference System (FIS)

**(ii) Knowledge base**

The inputs and output(s) associations are well defined by fuzzy conditional functions that are recognized as fuzzy 'IF & THEN' rules. A fuzzy conditional rule is usually made up of a premise (antecedent) and a consequent (conclusion) part for example "if $x$ is High (premise) then $y$ is Low (consequent)". Here, the terms High and Low are represented by MFs (Jang et al., 1997).

**iii) Inference Engine**

This is an important step of fuzzy expert system that combines and aggregates the evidences derived from the fuzzification process with the rule base (developed in previous steps). There are several fuzzy inference system reported so far in literature; but for the present work, Mamdani fuzzy model has been selected. This approach explores the theories of fuzzy sets and fuzzy logic to transform an entirely unstructured set of linguistic heuristics into an algorithm (Mamdani and Assilian, 1975). In other words, this step facilitates the use of Mamdani fuzzy 'IF & THEN' rules to develop a relationship between fuzzy inputs and fuzzy output(s). It is, therefore, called an inference engine that applies knowledge on the inputs and derives solutions as output(s). Fig. 7.1 shows a schematic diagram of a FIS and fuzzy rule base generation.

The general form of 'IF & THEN' rule formulated in Mamdani fuzzy model is given below (Eq. 7.1)

If $x_1$ is $A_{i1}$ and $x_2$ is $A_{i2}$ and… $x_r$ is $A_{ir}$ then $y$ is $B_i$ for $(i = 1; 2; K)$ (7.1)

where, $x_1$ is the input variable, $A_{ir}$ and $B_i$ are linguistic terms, $y$ is the output variable, and $K$ is the total number of rules. Further, *MAX-MIN* composition method is applied to establish the Mamdani fuzzy model. This method is mathematically defined as follows (Monjezi and Rezae, 2011):

$$\mu_{C_k}(Z) = \max[\min[\mu_{A_k}(Input(x)), \mu_{B_k}(input(y))]] \quad k = 1,..2,..,r \tag{7.2}$$

where, $\mu_{C_k}$, $\mu_{A_k}$ and $\mu_{B_k}$ are the membership functions of output $z$ for rule $k$, input $x$ and $y$ respectively.

**(iv) Defuzzifier**

Finally, the defuzzification process is used to convert fuzzy sets into crisp value. There are numerous defuzzifier approaches available in the literature. Centroid of Area (COA) method is the most common one for the purpose of defuzzification process. The benefit of the COA method is that all activated membership functions of the conclusions (all active rules) take part in the defuzzification process (Daftaribesheli et al., 2011). The COA method applies the following equation (Eq. 7.3) for transforming fuzzy structure into a crisp value (Iphar and Goktan, 2006):

$$Z^*COA = \frac{\int_z \mu_A(z) z \, dz}{\int_z \mu_A(z) \, dz} \tag{7.3}$$

where, $Z*COA$ is the crisp value for the $"z"$ output and, $\mu_A(z)$ is the aggregated output membership function.

## 7.4 Case Empirical Illustration

In the present business world, e-commerce appears to be very essential for an organization’s growth and existence. Globalization and participation of large number of business competitors in the marketplace have enforced companies to adapt e-commerce policy. In course of e-commerce execution, the security of EC system ensuring accurate and on-time transaction processing along with data safety has now become the prime concern for the organizations involved in such online trading. With technological advancement and increased level of threat and vulnerabilities resulted thereof; the organizations practicing e-commerce have to face some risks including internal as well as external risks.

In this work, an attempt has been made to identify potential risks responsible for incurring adverse impact on the expected success of e-commerce transaction for an Indian case company. To conduct the study, the decision making data have been collected in subjective terms from the expert panel consisting of five Decision-Makers. A questionnaire based survey has been conducted (refer to APPENDIX B). Fuzzy Set Theory (FST) has been used to tackle ambiguity and vagueness associated in human thoughts in assessing risk quantifying parameters (viz. likely hood of occurrence as well as impact) in a subjective way. Based on risk extent values corresponding to different risk sources, a total number of forty eight e-commerce risk factors have been categorized into five distinct levels representing their degree of severity (of adverse consequence). Thus, ‘critical’ risk factors have been identified. Appropriate corrective measures to mitigate e-commerce risks (under different levels of severity) have also been suggested in the present study.

Overall risk extent has then been computed by exploration of Fuzzy Inference System (FIS). Further, an ISM approach has been used in which a structural relationship diagram has been formed considering five identified risk sources under ‘critical’ level. MICMAC analysis has also been performed that has provided a guideline for classification of perceived e-commerce risks (critical risks) in four different quadrants/ clusters on the basis their driving and dependence power. The stepwise computation and results obtained thereof have been described below.

### 7.4.1 Categorization of Risks into Different Levels of Severity

The proposed risk assessment model has been empirically studied with reference to a case company located at South India. The unified aim of this study has been to find out the risk sources affecting e-commerce transactions utmost. In this study, linguistic scales have been utilized in order to access e-commerce risks in terms of its likelihood (probability) of occurrence and impact (consequence). Zhi (1995) and Samantra et al (2014) described risk (fuzzy risk extent $\tilde{R}_E$) as a function of two parameters – (i) the likelihood of occurrence $(\tilde{L}O)$, which is the possibility of an undesirable occurrence, and (ii) the impact $(\tilde{I})$, which is the degree of seriousness that is incurred when such desirable events take place. Thus, fuzzy risk extent can be calculated using a mathematical formulation as shown in Eq. (7.4).

$$\tilde{R}_E = \tilde{L}O \otimes \tilde{I} \tag{7.4}$$

It is hereby noticed from Eq. (7.4), that the risk extent is close to zero; if a risk factor has either less impact or less likelihood of occurrence. However, the risk extent will be close to one (i.e. more); if a risk factor possessing high impact and high likelihood of occurrence. In this equation, $\tilde{L}O$ and $\tilde{I}$ are defined within a range [0, 1] where high value of $\tilde{R}_E$ specifies high adverse impact on e-commerce performance, in the present context. It is hereby noticed from Eq. (7.4), that the 'crisp' risk extent $\left[crisp(\tilde{R}_E) = R_E\right]$ is close to zero; if a risk factor has either less impact or less likelihood of occurrence. However, the risk extent approaches close to unity; if a risk factor possessing high impact and high likelihood of occurrence. Here, $\tilde{L}O$ and $\tilde{I}$ both are expressed in terms of fuzzy numbers; and hence, multiplication of two fuzzy numbers yields another fuzzy number i.e. $\tilde{R}_E$ called as fuzzy risk extent.

According to Zimmermann (1991), linguistic data represented in words or sentences are very useful in dealing with situations that are too complex or ill-defined. Furthermore, to tackle Decision-Makers' vague and ambiguous representation of human thought, fuzzy set theory has been found appropriate to deal with many real life situations where available information is insufficient or ill-known. To fulfill the purpose, in the present study, five Decision-Makers (DMs) (company's stakeholders) have been selected carefully according to their experience, expertise and job profile.

The DMs have been requested to provide their response by utilizing the linguistic scales as shown in Table 7.1. Total forty eight risk sources have been identified through several brainstorming sessions executed by the company's stakeholders (Table 7.2). Against each risk source, corresponding likelihood of occurrence and impact as provided by the DMs (expressed in linguistic terms) have been obtained and shown in Table 7.2. Subjective linguistic data have further been transformed into appropriate positive triangular fuzzy numbers as prescribed in Table 7.1. Decision-Makers' response (multi-judge) has been combined in next step by using fuzzy aggregation rule to obtain pulled opinion of the decision making group. The application of fuzzy arithmetic operational rules have been found necessary at this stage to perform fuzzy based quantitative risk analysis.

Fuzzy aggregation is a process by which the fuzzy sets are combined into a single collective preference (fuzzy value). Let $k$ is the number of decision makers $(DM_t \,|t=1,...,k)$; responsible for assessing a total number of $m$ e-commerce risk sources $(R_i, i=1,....,m)$. Assuming $\tilde{x}_i^t$ be the fuzzy preference value (against likelihood of occurrence) for a particular risk source $R_i$ given by the $t^{th}$ DM i.e. $DM_t$, the aggregated fuzzy preference $\tilde{x}_i$ against risk source $R_i$ (i.e. $\tilde{L}O_i$) can be computed by fuzzy average rule (Chen, 2000);

$$\tilde{L}O_i = \tilde{x}_i = \frac{1}{k}\left[\tilde{x}_i^1 \oplus \tilde{x}_i^2 \oplus ... \oplus \tilde{x}_i^k\right] \tag{7.5}$$

Similarly, assuming $\tilde{q}_i^t$ be the fuzzy preference value (against impact of occurrence) for a particular risk source $R_i$ given by the $t^{th}$ DM i.e. $DM_t$, the aggregated fuzzy preference $\tilde{q}_i$ against risk source $R_i$ (i.e. $\tilde{I}_i$) can be computed by the same formulation shown below.

$$\tilde{I}_i = \tilde{q}_i = \frac{1}{k}\left[\tilde{q}_i^1 \oplus \tilde{q}_i^2 \oplus ... \oplus \tilde{q}_i^k\right] \tag{7.6}$$

The following relation can be used for calculating the fuzzy risk extent $\tilde{R}_{E_i}$ against each of the risk sources under consideration.

$$\tilde{R}_{E_i} = (\tilde{x}_i) \otimes (\tilde{q}_i) = \tilde{L}O_i \otimes \tilde{I}_i \tag{7.7}$$

Aggregated fuzzy preferences (in relation to likelihood $\tilde{L}O_i$ and impact $\tilde{I}_i$ $(i = 1,2,\ldots,48)$against individual risk sources) and corresponding risk extent $\left(\tilde{R}_{E_i}\right)$ for forty eight risk sources have been calculated using Eqs. (7.5), Eq. (7.6) and Eq. (7.7), respectively; and shown in Table 7.3. For risk source $R_i$, the likelihood $\left(\tilde{L}O_i\right)$ has been multiplied by the impact factor $(\tilde{I}_i)$; and, the consequence of their product i.e. fuzzy risk extent $\left(\tilde{R}_{E_i}\right)$ has also been represented as another positive triangular fuzzy number. The 'crisp equivalent' risk extent for the risk factor $R_i$ has been computed using (Eq. 7.4) and treated as crisp risk rating. The crisp ratings (risk extent) against forty eight risk sources have thus been computed and tabulated in Table 7.3.

From the linguistic scales chosen for assessing expert opinion in terms of likelihood of occurrence and impact (against individual risk sources) and converting them into appropriate fuzzy numbers representation; Eq. (7.4), has been explored to define a scale (based on crisp risk rating) for categorization of various risk factors into some distinct level of severity. In this case, the range of crisp risk ratings has appeared as (0.009 to 0.902); and, this has been partitioned into five distinct levels (as suggested by the expert team) for categorization of various risk factors based on their severity degree towards imposing adverse effect on e-commerce performance in relation to the case company.

Thus, e-commerce risk influencing factors (risk sources) as listed in Table 7.1 have now been categorized into five different severity levels (as shown in Table 7.4) viz. Negligible (0.009- 0.099), Minor (0.100-0.199), Marginal (0.200-0.299), Critical (0.300-0.399) and Catastrophic (0.400-0.902). In this case empirical analysis, none of the risk sources have found coming under the catastrophic level. Therefore, the risk sources belonging to the critical level (viz. R10, R13, R17, R18, R19) have been understood as the risk sources affecting the company's e-commerce performance utmost (as shown in Table 7.7). In other words, these risks have been considered as critical risks which need to be monitored carefully to reduce the probability of occurrence and thereby mitigate future threat of disruption/interruption in e-commerce practices for the particular case company. Finally, an action requirement plan has been prescribed on the basis of severity (corresponding to each level; as shown in Table 7.4) of potential risk sources by the company's Risk Management Team Lead, Risk Owner, Risk Committee, and Decision Team etc. for prompt identification and adaptation to specific managerial strategies towards mitigating e-commerce risks appeared at different levels of severity. The identification of various risk influencing factors under each categories and possible action requirement plans as suggested by the decision making team have also been illustrated in Table 7.4.

### 7.4.2 Computation of Overall Risk Extent

In the next phase, an attempt has been made to evaluate a quantitative index to present overall risk extent in relation to e-commerce being executed by the case company. This unique quantitative index has been denoted as Fuzzy Overall Risk Index (FORI) $\left(\tilde{R}_E\right)_O$; and, when converted to equivalent crisp score it is termed as crisp overall risk index i.e. $\left(R_E\right)_O$. Computation of overall risk index (either in terms of fuzzy number or converted crisp score) requires aggregation (weighted average) of risk extents (rating i.e. $\tilde{R}_{E_i}\big|i=1,2,...,5$) of individual risk sources $R_i\big|i=1,2,...,5$ (considering five risk sources only that belong to critical level of severity) in consideration with their priority weights. Since assignment of 'exact' weights to different risk sources is indeed a difficulty. To overcome this shortcoming, FIS has been applied to aggregate risk extent values of different risk sources to compute a unique index i.e. overall risk extent.

In the proposed Fuzzy Inference System (FIS), risk sources, identified under 'critical' level (R10, R13, R17, R18, R19), have been considered as input parameters to predict the overall risk extent $(R_E)_O$. The crisp risk extent $(R_{E_i})$ values of individual risk sources R10, R13, R17, R18 and R19 (as shown in Table 7.5) have been fuzzified first. Membership Functions (MFs) for each of the risk sources (viz. R10, R13, R17, R18, R19) have been selected as: Tolerant (T), Moderate (M), and Extreme (E). Whereas, Membership Functions (MFs) to describe fuzzy overall risk extent (as FIS output) have been selected as: Less Tolerant (LT), Tolerant (T), Moderate (M), Extreme (E) and Absolutely Extreme (AE). Proposed FIS architecture has been shown in Fig. 7.2. Membership Functions (MFs) of input parameter (say, risk extent of R9) have been shown in Fig. 7.3. The MFs of other four risk sources (R13, R17, R18, R19) have been the same as R10; and hence, not shown here. Similarly, Membership Functions (MFs) for overall risk extent $(\tilde{R}_E)_O$ have been shown in Fig. 7.4. A total 243 numbers of fuzzy approximate reasoning rules have been constructed and fed to the inference engine for adequate understanding of inputs-output mapping by the FIS (refer to Fig. 7.5). The fuzzy rule base explored herein has been provided in APPENDIX C. By exploring such rule base, the fuzzy overall risk extent $(\tilde{R}_E)_O$ has been obtained through FIS. Finally, $(\tilde{R}_E)_O$ has been defuzzided by the COA method (using Eq. 7.3) to obtain equivalent crisp overall risk extent $(R_E)_O$ = 0.33 (as shown in Fig. 7.6). The crisp value of the overall risk extent represents the level (condition) of risk (future threat) presently existing associated with company's e-commerce transactions.

The advantage of such computation may be articulated that the value of overall risk extent can be used to compare existing scenario of different companies executing e-commerce of similar fashion. Lower the value of overall risk extent leads to the minimum e-commerce risk and hence high probability towards e-commerce success. From amongst the set of candidate companies, the company which corresponds to the minimum overall risk extent can be considered as the best; and, the practices towards e-commerce risk mitigation followed by the same may be treated as benchmark solution practices for possible risk avoidance for the follower companies.

### 7.4.3 Development of ISM Model: Interrelationship Amongst Critical Risk Factors

Finally, risk sources belong to critical level of severity (viz. R10, R13, R17, R18, R19) have been considered again for the analysis through ISM. Following the procedural steps as prescribed in ISM literature (refer to **Chapter 6**; **Section 6.3.2**). Structural Self-Interaction Matrix (SSIM) has been developed as shown in Table 7.6. Final reachability matrix has thus been obtained (shown in Table 7.6). Driver power and dependence power has been carried out next along and tabulated in Table 7.7. Level partitioning of aforementioned five critical risk sources has now been achieved; and, the summary of level partitioning has been shown in Table 7.8. Then, MICMAC analysis has been performed; all five critical risk sources have been placed into their appropriate quadrants (as shown in Fig. 7.7) viz. autonomous, dependent, linkage and driver.

Autonomous is the risk factor which have weak driving power and weak dependence power. It has been found that there is no risk source coming under autonomous group.

Dependent is the risk factor which have weak driving power and strong dependence power. Risk sources R13 and R19 have appeared to be present in this quadrant. Linkage risk factors should have both strong driving and dependence power; no one has placed in this quadrant. Driver risk factors should correspond to strong driving power but weak dependence power; risk factors R10, R17 and R18 have appeared in this quadrant. Further, the ISM has been used to establish the relationship amongst various risk sources under 'critical' level; a relationship diagram (ISM model) has been developed (in hierarchical form) and shown herein in Fig. 7.8.

Developed ISM model has segregated e-commerce risk sources (viz. R10, R13, R17, R18, R19) into a hierarchy of four different levels. Level-I includes R13 (Site or network overload and disruption) and R19 (Continuous change of system requirements). Level-II encounters R10 (Threat of sabotage in internal network). R18 (Technological newness) is placed under Level-III and finally R17 (Project complexity) appears at Level-IV of the said hierarchical model.

## 7.5 Concluding Remarks

Based on the results, it can be concluded that the developed model found quite fruitful towards assessment of risks associated with company's e-commerce practices. The risk management team is hereby suggested to monitor potential risk sources frequently with undertaking of appropriate action requirement plans as discussed in this part of work. The model is found helpful to examine the severity of potential risk sources and these can be categorized into appropriate levels. This sort of categorization may definitely help the company's risk management team to develop a proactive risk mitigation plan. The risk analysis team is hereby suggested to transfer the information on risk escalating issues as soon as possible to the relevant authority for rescheduling of certain tasks in order to maintain a risk-free e-commerce execution. Apart from this, a policy to control risk between the enterprises, internal risk and external risk must be outlined in order to ensure integrity, authenticity and confidentiality of the data and the operation involved in exercising e-commerce. In severely risky situation, the e-commerce activities may be postponed (or kept in held) until risk is dropped to a tolerable limit. This practice may limit the overall risk extent with a potential future growth in the performance of e-commerce.

The conclusions drawn from the case empirical study have been summarized below.

1. Out of forty eight risk sources selected for e-commerce risk assessment, it has been found that the following risks viz. R10 (Threat of sabotage in internal network), R13 (Site or network overload and disruption), R17 (Project complexity), R18 (Technological newness), and R19 (Continuous change of system requirements) are considered as 'critical' risks. No such risk with severity level 'catastrophic' has been observed in relation to the e-commerce practice of the case company.

2. FIS has been implemented to find out the overall risk extent for the case company (considering critical risks only) and the value obtained is 0.33.

3. Moreover, a structural relationship amongst the perceived e-commerce risks under 'critical' level has been established through application of ISM approach for adequate understanding of risks so that it can be avoided in adapting proper action requirement plans in course of future e-commerce transactions.

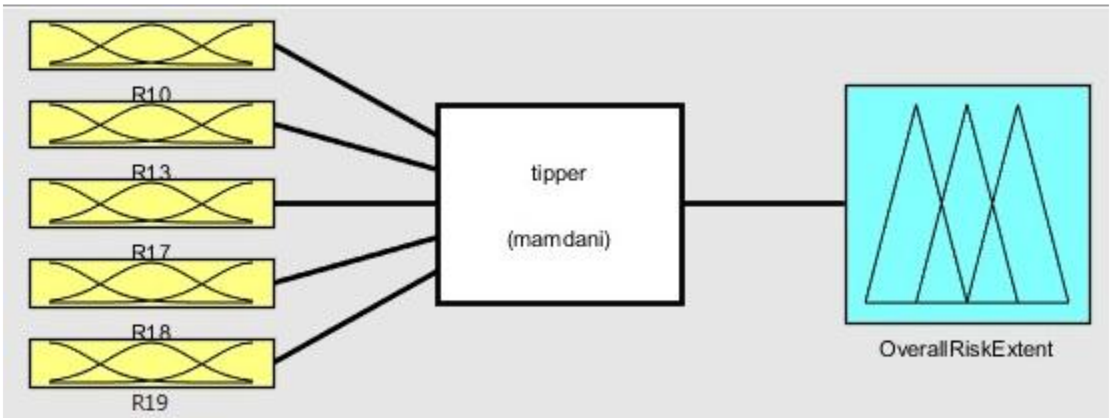


Fig. 7.2: Proposed FIS architecture

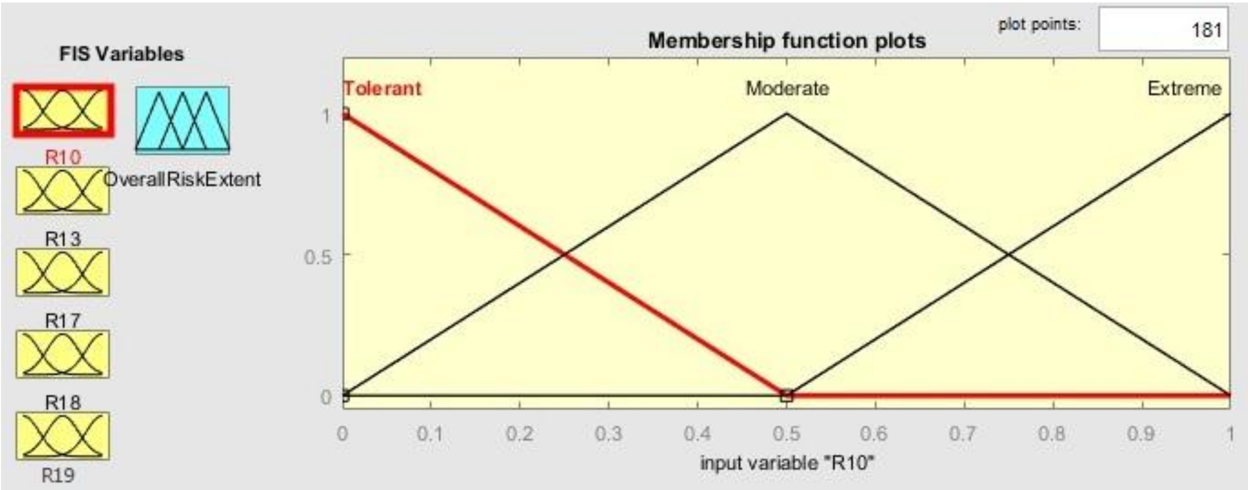


Fig. 7.3: Membership Functions (MFs) for representing fuzzified risk extent of R10

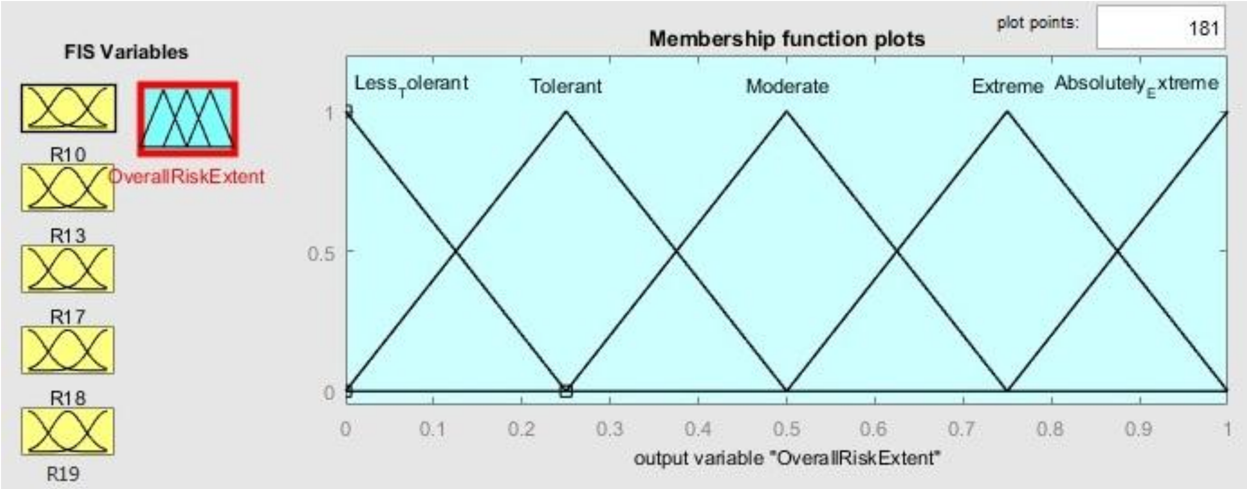


Fig. 7.4: Membership Functions (MFs) for evaluating Fuzzy Overall Risk Extent (FORE)

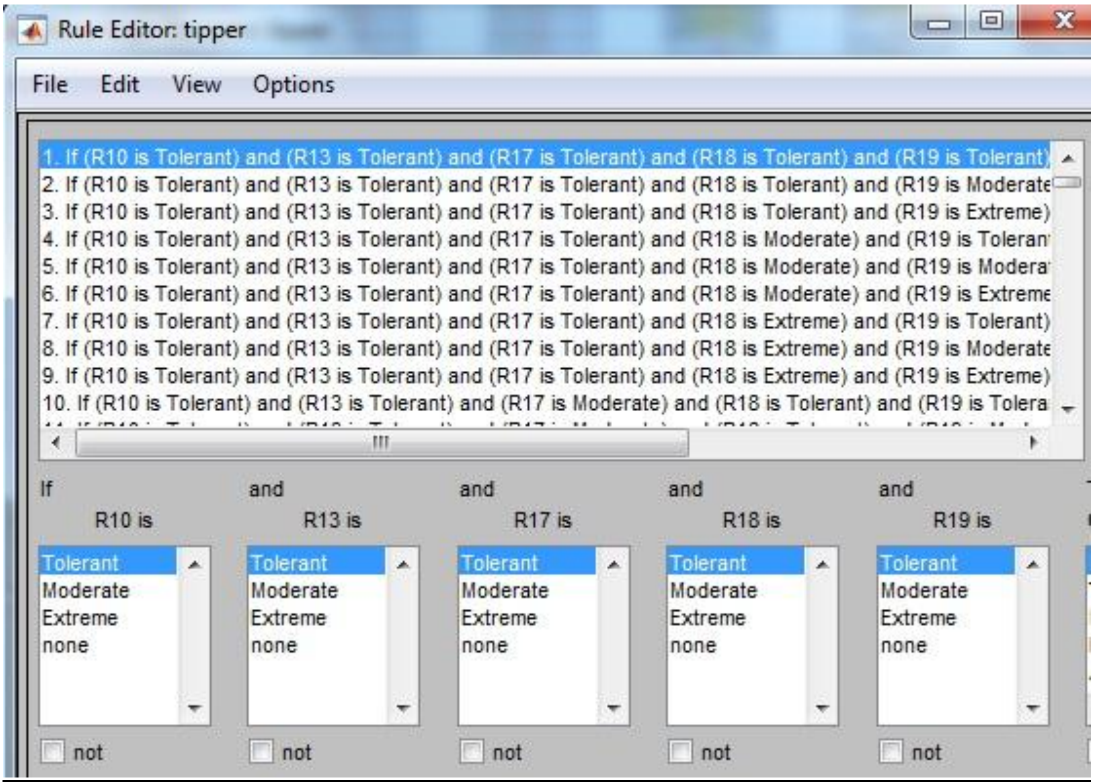


Fig. 7.5: Fuzzy rule base

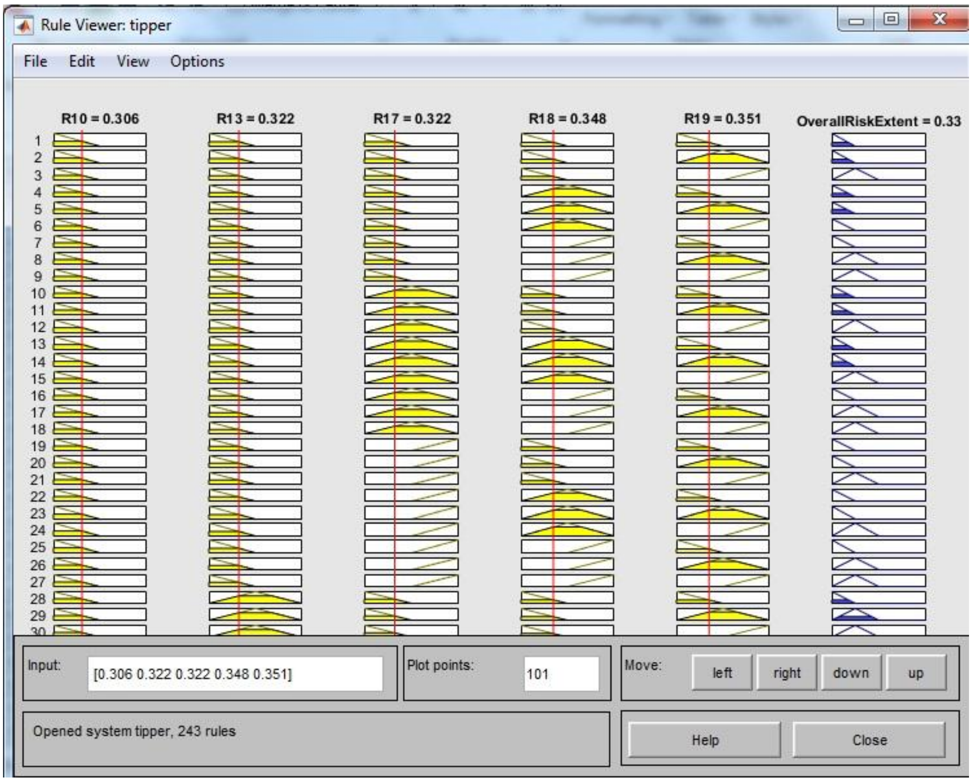


Fig. 7.6: Computation of crisp overall risk extent by exploring fuzzy approximate reasoning

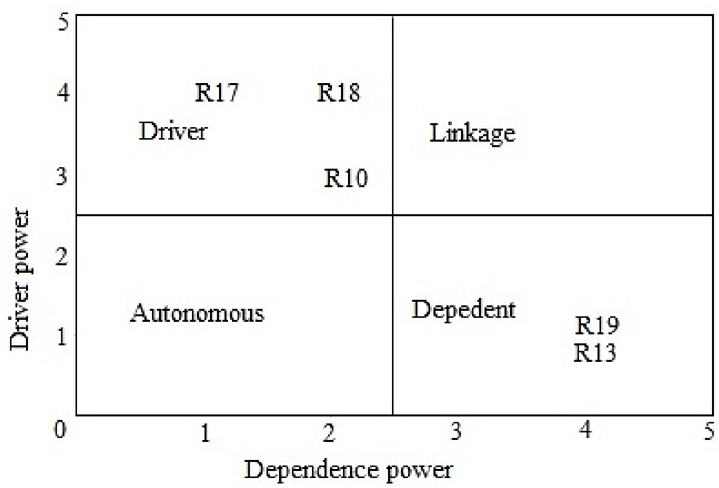


Fig. 7.7: Driver power and dependence power matrix

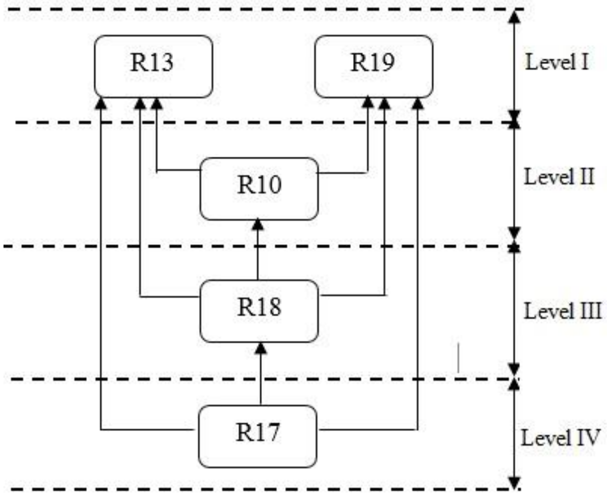


Fig. 7.8**:** Interpretive Structural Model (ISM) for e-commerce risk sources under critical level of severity

Table 7.1: Linguistic variables for assignment of (a) likelihood of occurrence and (b) impact against individual risks

| Likelihood of occurrence | Impact of risk occurrence | Fuzzy representation<br>(Positive triangular fuzzy numbers) |
|---|---|---|
| Absolutely Rare (AR) | Absolutely Low (AL) | (0,0,0.16) |
| Very Rare (VR) | Very Low (VL) | (0,0.16,0.34) |
| Rare (R) | Low (L) | (0.16,0.34,0.5) |
| Often (O) | Moderate (M) | (0.34,0.5,0.66) |
| Frequent (F) | Serious (S) | (0.5,0.66,0.84) |
| Very Frequent (VF) | Critical (C) | (0.66,0.84,1) |
| Highly Frequent (HF) | Highly Critical (HC) | (0.84,1,1) |

Table 7.2: Subjective data expressed in linguistic terms as given by the DMs against individual risk sources for the case company

| Sl. No. | Potential risk sources $R_i \mid i = 1,2,...,48$ | Likelihood of Occurrence | | | | | Impact | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $DM_1$ | $DM_2$ | $DM_3$ | $DM_4$ | $DM_5$ | $DM_1$ | $DM_2$ | $DM_3$ | $DM_4$ | $DM_5$ |
| 1 | Hacker gaining unauthorized access | AR | AR | AR | AR | HF | HC | C | HC | HC | HC |
| 2 | Absence of firewall | AR | AR | VR | AR | VF | HC | HC | HC | C | C |
| 3 | Lack of using cryptography | VR | VR | VR | VR | VF | HC | C | C | C | HC |
| 4 | Poor ‘‘key’’ management | VR | AR | R | VR | VF | C | C | C | HC | HC |
| 5 | Malicious code attacks | VR | R | VR | O | F | C | HC | S | S | S |
| 6 | Disclosure of sensitive information | VR | AR | R | VR | VF | C | C | C | HC | HC |
| 7 | Loss of audit trail | R | AR | VR | R | F | C | HC | C | S | C |
| 8 | Natural disaster-caused equipment failure | R | AR | R | R | O | C | C | S | S | C |
| 9 | Human factor-caused equipment failure | R | VR | VR | R | O | M | S | S | C | C |
| 10 | Threat of sabotage in internal network | VR | O | R | R | F | S | M | C | S | HC |
| 11 | Inadequate backup systems | AR | F | VR | VR | F | HC | M | S | S | C |
| 12 | Software or hardware problem-caused system failure | VR | VR | VR | O | F | C | M | S | S | HC |
| 13 | Site or network overload and disruption | VR | F | R | O | O | S | M | S | C | C |
| 14 | Poor design, code or maintenance procedure | R | VR | R | VR | F | C | S | C | C | C |
| 15 | Wrong functions and properties development | R | AR | VR | R | R | S | S | C | HC | S |
| 16 | Wrong user interface development | R | AR | AR | R | O | S | C | HC | HC | S |
| 17 | Project complexity | R | VF | R | VR | O | S | S | C | S | S |
| 18 | Technological newness | O | F | O | R | F | M | S | HC | M | M |
| 19 | Continuous change of system requirements | O | O | O | VR | VF | S | C | C | M | M |
| 20 | Wrong schedule estimation | R | R | R | VR | O | S | S | S | S | M |
| 21 | Project behind schedule | VR | R | VR | VR | R | VL | S | S | S | M |
| 22 | Project over budget | R | O | AR | VR | VR | M | S | C | C | M |
| 23 | Inadequate cash flow | VR | AR | VR | R | O | L | S | S | C | M |
| 24 | Personnel shortfalls | R | O | R | VR | O | M | C | S | S | M |

Table 7.2 (continued): Subjective data expressed in linguistic terms as given by the DMs against individual risk sources for the case company

| Sl. No. | Potential risk sources $R_i \| i = 1,2,...,48$ | Likelihood of Occurrence | | | | | Impact | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $DM_1$ | $DM_2$ | $DM_3$ | $DM_4$ | $DM_5$ | $DM_1$ | $DM_2$ | $DM_3$ | $DM_4$ | $DM_5$ |
| 25 | Lack of expertise and experience in e-commerce | R | F | R | R | R | M | S | C | S | S |
| 26 | Loss of key person | R | O | VR | O | VR | S | C | HC | C | S |
| 27 | Lack of top management support | R | R | VR | VR | VR | L | S | C | S | S |
| 28 | Poor project planning | R | VR | R | VR | O | S | C | C | S | S |
| 29 | Loss of control over vendor | VR | VR | VR | VR | O | S | C | C | S | C |
| 30 | Indefinite project scope | VR | O | VR | VR | F | S | S | S | S | C |
| 31 | Lack of contingency plans | VR | R | R | R | O | S | S | S | C | C |
| 32 | Business process redesign | R | VR | R | R | F | C | S | C | S | M |
| 33 | Organizational restructuring | R | AR | VR | VR | O | C | S | C | M | L |
| 34 | Lack of trust between organization and merchant or customer | VR | VR | VR | VR | R | S | C | S | C | L |
| 35 | Inappropriate media for the product and service | R | VR | R | R | R | C | C | C | HC | M |
| 36 | Lack of international legal standards | AR | AR | AR | VR | VR | HC | HC | HC | HC | |
| 37 | New laws, regulations, and judicial decisions constantly change the online legal landscape | VR | AR | AR | O | F | HC | HC | HC | C | M |
| 38 | Uncertain legal jurisdiction | VR | AR | AR | VR | R | C | HC | HC | C | S |
| 39 | Incompletion of contract terms | VR | AR | VR | VR | VR | C | S | C | S | C |
| 40 | Loss of data control | AR | AR | VR | VR | R | HC | HC | S | C | HC |
| 41 | Loss of control over information technology | VR | AR | VR | VR | R | C | S | C | C | HC |
| 42 | Hidden cost | VR | R | R | O | VR | S | M | S | M | L |
| 43 | Unclear project objectives | R | O | VR | VR | AR | S | S | C | S | S |
| 44 | Lack of vendor expertise and experience | VR | O | R | R | AR | M | S | C | C | S |
| 45 | Lock-in situation | R | R | VR | R | VR | S | M | S | S | S |
| 46 | Vendor offers outdated technology skill | R | VR | VR | O | VR | S | L | S | M | C |
| 47 | Different users with difference in culture customers, and business style | R | VR | AR | F | VR | VL | VL | VL | S | C |
| 48 | Language barrier | R | AR | AR | F | F | L | AL | AL | M | C |

Table 7.3: Aggregated fuzzy preferences for individual risk sources and corresponding risk extent (fuzzy and crisp representation both)

| $R_i$ | $\widetilde{LO}_i$ | $\widetilde{I}_i$ | $\widetilde{R}_{E_i}$ | $R_{E\,i}$ | $R_i$ | $\widetilde{LO}_i$ | $\widetilde{I}_i$ | $\widetilde{R}_{E_i}$ | $R_{E\,i}$ |
|---|---|---|---|---|---|---|---|---|---|
| **R1** | (0.168,0.200,0.328) | (0.804,0.968,1.000) | (0.135,0.194,0.328) | 0.219 | **R25** | (0.228,0.404,0.568) | (0.500,0.664,0.836) | (0.114,0.268,0.475) | 0.286 |
| **R2** | (0.132,0.200,0.364) | (0.768,0.936,1.000) | (0.101,0.187,0.364) | 0.218 | **R26** | (0.168,0.332,0.500) | (0.632,0.800,0.936) | (0.106,0.266,0.468) | 0.280 |
| **R3** | (0.132,0.296,0.472) | (0.732,0.904,1.000) | (0.097,0.268,0.472) | 0.279 | **R27** | (0.064,0.232,0.404) | (0.464,0.632,0.804) | (0.030,0.147,0.325) | 0.167 |
| **R4** | (0.164,0.300,0.468) | (0.732,0.904,1.000) | (0.120,0.271,0.468) | 0.286 | **R28** | (0.132,0.300,0.468) | (0.564,0.732,0.904) | (0.074,0.220,0.423) | 0.239 |
| **R5** | (0.200,0.364,0.536) | (0.600,0.764,0.904) | (0.120,0.278,0.485) | 0.294 | **R29** | (0.068,0.228,0.404) | (0.596,0.768,0.936) | (0.041,0.175,0.378) | 0.198 |
| **R6** | (0.164,0.300,0.468) | (0.732,0.904,1.000) | (0.120,0.271,0.468) | 0.286 | **R30** | (0.168,0.328,0.504) | (0.532,0.696,0.872) | (0.089,0.228,0.439) | 0.252 |
| **R7** | (0.164,0.300,0.468) | (0.664,0.836,0.968) | (0.109,0.251,0.453) | 0.271 | **R31** | (0.164,0.336,0.500) | (0.564,0.732,0.904) | (0.092,0.246,0.452) | 0.263 |
| **R8** | (0.164,0.304,0.464) | (0.596,0.768,0.936) | (0.098,0.233,0.434) | 0.255 | **R32** | (0.196,0.368,0.536) | (0.532,0.700,0.868) | (0.104,0.258,0.465) | 0.276 |
| **R9** | (0.132,0.300,0.468) | (0.532,0.700,0.868) | (0.070,0.210,0.406) | 0.229 | **R33** | (0.100,0.232,0.400) | (0.464,0.636,0.800) | (0.046,0.148,0.320) | 0.171 |
| **R10** | (0.232,0.400,0.568) | (0.568,0.732,0.868) | (0.132,0.293,0.493) | 0.306 | **R34** | (0.032,0.196,0.372) | (0.496,0.668,0.836) | (0.016,0.131,0.311) | 0.153 |
| **R11** | (0.200,0.328,0.504) | (0.568,0.732,0.868) | (0.114,0.240,0.437) | 0.264 | **R35** | (0.128,0.304,0.468) | (0.632,0.804,0.932) | (0.081,0.244,0.436) | 0.254 |
| **R12** | (0.168,0.328,0.504) | (0.568,0.732,0.868) | (0.095,0.240,0.437) | 0.266 | **R36** | (0.000,0.064,0.232) | (0.740,0.900,0.932) | (0.000,0.058,0.216) | 0.091 |
| **R13** | (0.268,0.432,0.600) | (0.532,0.700,0.868) | (0.143,0.302,0.521) | 0.322 | **R37** | (0.168,0.264,0.432) | (0.704,0.868,0.932) | (0.118,0.229,0.403) | 0.250 |
| **R14** | (0.164,0.332,0.504) | (0.628,0.804,0.968) | (0.103,0.267, 0.488) | 0.286 | **R38** | (0.032,0.132,0.300) | (0.700,0.868,0.968) | (0.022,0.115,0.290) | 0.142 |
| **R15** | 0.096,0.236,0.400) | (0.600,0.764,0.904) | (0.058,0.180,0.362) | 0.200 | **R39** | (0.000,0.128,0.304) | (0.596,0.768,0.936) | (0.000,0.098,0.285) | 0.128 |
| **R16** | (0.132,0.236,0.396) | (0.668,0.832,0.936) | (0.088,0.196,0.371) | 0.218 | **R40** | (0.032,0.132,0.300) | (0.736,0.900,0.968) | (0.024,0.119,0.290) | 0.144 |
| **R17** | (0.264,0.436,0.600) | (0.532,0.696,0.872) | (0.140,0.303,0.523) | 0.322 | **R41** | (0.032,0.164,0.336) | (0.664,0.836, 0.968) | (0.021,0.137,0.325) | 0.161 |
| **R18** | (0.368,0.532,0.700) | (0.472,0.632,0.764) | (0.174,0.336,0.535) | 0.348 | **R42** | (0.132,0.300,0.468) | (0.368,0.532,0.700) | (0.049,0.160,0.328) | 0.179 |
| **R19** | (0.336,0.500,0.664) | (0.500,0.668,0.832) | (0.168,0.334,0.552) | 0.351 | **R43** | (0.100,0.232,0.400) | (0.532,0.696,0.872) | (0.053,0.161,0.349) | 0.188 |
| **R20** | (0.164,0.336,0.500) | (0.468,0.628,0.804) | (0.077,0.211,0.402) | 0.230 | **R44** | (0.132,0.268,0.432) | (0.532,0.700,0.868) | (0.070,0.188,0.375) | 0.211 |
| **R21** | (0.064,0.232,0.404) | (0.368,0.528,0.704) | (0.024,0.122,0.284) | 0.143 | **R45** | (0.096,0.268,0.436) | (0.468,0.628,0.804) | (0.045,0.168,0.351) | 0.188 |
| **R22** | (0.100,0.232,0.400) | (0.500,0.668,0.832) | (0.050,0.155,0.333) | 0.179 | **R46** | (0.100,0.264,0.436) | (0.432,0.600,0.768) | (0.043,0.158,0.335) | 0.179 |
| **R23** | (0.100,0.232,0.400) | (0.432,0.600,0.768) | (0.043,0.139,0.307) | 0.163 | **R47** | (0.132,0.264,0.436) | (0.232,0.396,0.572) | (0.031,0.105,0.249) | 0.128 |
| **R24** | (0.200,0.368,0.532) | (0.468,0.632,0.800) | (0.094,0.233,0.426) | 0.251 | **R48** | (0.232,0.332,0.500) | (0.232,0.336,0.496) | (0.054,0.112,0.248) | 0.138 |

$R_i \sim i^{th}$ Risk source; $\widetilde{LO}_i$ ~aggregated fuzzy likelihood of occurrence; $\widetilde{I}_i$ ~aggregated fuzzy impact; $\widetilde{R}_{E_i}$ ~fuzzy risk extent; $R_{E\,i}$ ~crisp risk extent (refer Table 7.3)

Table 7.4: Categorization of potential risk factors into different levels of severity: Action requirement plans

| Severity level | Range of risk extent (crisp) | Identified risks | Action(s) required |
|---|---|---|---|
| Negligible | 0.009- 0.099 | R36 | Accept and monitor risk. These risks are considered acceptable and need no serious action. However, decision team must ensure that the controls are maintained. |
| Minor | 0.100-0.199 | R21, R22, R23, R27, R29, R33, R34, R38, R39, R40, R41, R42, R43, R45, R46, R47, R48 | Timely investigation is required for further possible action. The risk reduction measure should be implemented within a certain period. Minor corrections required. Arrangement should be made to ensure that controls are maintained. . |
| Marginal | 0.200-0.299 | R1, R2, R3, R4, R5, R6, R7, R8, R9, R11, R12, R14, R15, R16, R20, R24, R25, R26, R28, R30, R31, R32, R35, R37, R44 | Prompt notification of risk is required. Adjust business requirements or constraints to eliminate or reduce the risk. Manage and monitor risk, ensure that the controls are maintained and inform senior management. |
| Critical | 0.300-0.399 | R10, R13, R17, R18, R19, | Unacceptable risk sources, significant changes required. Immediate action must be taken. Team members have to do thorough research to control the risk. Extensive senior management involvement is required. The work activity should be halted until risk controls are implemented. |
| Catastrophic | 0.400-0.902 | Not Found | Unacceptable risk sources, significant changes required. Decision team must be placed on high alert. Team must discuss for re-scheduling of certain task. Implement actions immediately to minimize likelihood as well as impact of the risk. If it is not possible to control the risk, the work should be prohibited. |

Table 7.5: Equivalent crisp risk extent against critical risk sources (from Table 7.10)

| Critical risks | $R_E$ (crisp score) |
|---|---|
| R10 | 0.306 |
| R13 | 0.322 |
| R17 | 0.322 |
| R18 | 0.348 |
| R19 | 0.351 |

Table 7.6. Structural Self-Interaction Matrix (SSIM)

| Risks | R19 | R18 | R17 | R13 |
|---|---|---|---|---|
| R10 | V | A | O | V |
| R13 | O | A | A | * |
| R17 | V | V | * | * |
| R18 | V | * | * | * |

Table 7.7. Final reachability matrix with driving and dependence power

| Risks | R10 | R13 | R17 | R18 | R19 | Driver power |
|---|---|---|---|---|---|---|
| R10 | 1 | 1 | 0 | 0 | 1 | 3 |
| R13 | 0 | 1 | 0 | 0 | 0 | 1 |
| R17 | 0 | 1 | 1 | 1 | 1 | 4 |
| R18 | 1 | 1 | 0 | 1 | 1 | 4 |
| R19 | 0 | 0 | 0 | 0 | 1 | 1 |
| Dependence power | 2 | 4 | 1 | 2 | 3 | 13/13 |

Table 7.8. Summary of level partitioning

| Risks | Reachability set $R(s_i)$ | Antecedent set $A(s_i)$ | Intersection set $(R(s_i) \cap A(s_i))$ | Level |
|---|---|---|---|---|
| R10 | R10,R13,R19 | R10,R18 | R10 | II |
| R13 | R13 | R10,R13,R17,R18 | R13 | I |
| R17 | R13,R17,R18,R19 | R17 | R19 | IV |
| R18 | R10,R13,R18,R19 | R17,R18 | R19 | III |
| R19 | R19 | R17,R18,R19,R10 | R19 | I |

## Chapter 8

# Summary and Conclusions

Decision making deals with selecting the best alternative amongst available candidate alternatives by considering a set of evaluation criteria. Decision making in which criteria data are fully quantitative can easily be solved by traditional tools and techniques. However, real world decision making problems are usually too complex due to involvement of ill-defined (vague) criteria and related information which cannot be analyzed by traditional decision making approaches.

During decision making, subjectivity of evaluation information (human judgment) often creates conflict and bears some sort of uncertainties (ambiguity and vagueness). However, literature depicts that fuzzy/grey set theory can fruitfully overcome this problem. Hence, the present work attempts to explore generalized fuzzy numbers set as well as grey numbers set theories to deal with incompleteness, inconsistency and imprecision in human decision making by considering linguistic preferences of the Decision-Makers (DMs).

The work has aimed to develop decision support procedural hierarchies, and implementation through various case empirical studies in relation to industrial context (robot selection, g-resilient supplier selection, 3PL service provider selection, performance assessment of ecosilient supply chain etc.). Additionally, the work has intended to conceptualize Fuzzy based Multi-Criteria Group Decision Making (FMCGDM) framework for quantifying severity of risks associated in E-Commerce (EC) execution in business context. Application potential of various decision support modules proposed herein have also been compared to that of existing decision support approaches, available in literature resource.

Executive **summary** and **conclusions** of the work reported in the present dissertation have been pointed out below.

In relation to industrial robot selection (attempted in ***Chapter 3***), two case illustrations have been demonstrated by using fuzzy-TODIM approach viz. (i) considering subjective data set and, (ii) data set with a combination of subjective and objective data. The ranking order of alternative robots as obtained through Fuzzy-TODIM against six evaluation criteria has been obtained as $A_1>A_2>A_3>A_4$. Moreover, to examine application potential of the proposed fuzzy-TODIM, result obtained has been compared to that of fuzzy-TOPSIS. The ranking order obtained in Fuzzy-TOPSIS under the same data set has been found almost similar to that of Fuzzy-TODIM (the best choice and the worst choice appears the same; $A_1>A_3>A_2>A_4$) to that of Fuzzy-TODIM. The work has further contributed towards selection of industrial robot by applying fuzzy 'Degree of Similarity (DOS)' concept while establishing formulations of the proposed DSS in conjugation with Fuzzy-TODIM in order to measure the dominance between two alternative pair against a particular selection criterion.

In another part of work on robot selection, grey numbers set theory has been integrated with crisp-TODIM concept to tackle vague and ambiguous subjective data in regards of ill-defined evaluation criteria and, thereof, to rank candidate robot alternatives. A case empirical illustration has been provided to demonstrate the application potential of the proposed grey-TODIM approach. Four alternative robots ($S_1$, $S_2$, $S_3$ and $S_4$) have been studied against six robot selection criteria, through the grey-TODIM approach; and, the ranking order has appeared as $S_3>S_4>S_2>S_1$. A comparative analysis of the results obtained through grey-TODIM has been illustrated through the application of existing grey based decision making approaches: [Li's approach (Li et al., 2007b), grey-TOPSIS, Jadidi's approach (Jadidi et al., 2008)]. In all cases, the most appropriate choice has appeared the same.

Industrial robot selection has further been attempted by integrating fuzzy numbers set theory with PROMETHEE approach. An integrated decision making module has been developed (named as Fuzzy extended PROMETHEE) with the capability to deal with qualitative (subjective) data as well as quantitative (objective) data, simultaneously. In this work, the PROMETHHE I and II approaches have been modified to work under fuzzy environment facilitating an industrial robot selection problem. The proposed approach has been validated empirically through a case illustration by considering seven alternative robots ($R_1$, $R_2$, $R_3$, $R_4$, $R_5$, $R_6$, $R_7$) along with thirteen robot selection criteria (combination of subjective as well as objective criteria). Robot alternative $R_1$ has been ranked 'first' by applying the proposed fuzzy extended PROMETHEE approach,

($R_1$>$R_2$>$R_3$>$R_5$>$R_7$>$R_4$>$R_6$).

The work (executed ***Chapter 4***) has provided a novel TODIM based decision support framework in order to select the best 'g-resilient' supplier by considering 'green' as well as 'resiliency' criteria. In TODIM, dominance between two alternatives is converted into corresponding gain/loss by means of prospect function and includes reference criteria weight, relative weight, attenuation factor etc. In contrast to this, the proposed decision support system has followed straightforward and simple computational steps to derive final ranking order of candidate alternatives. To validate the model, a case empirical illustration has been provided by evaluating four alternative suppliers ($S_1$, $S_2$, $S_3$ and $S_4$) against fifteen supplier selection criteria (combination of green as well as resilient criteria). The proposed approach has been depicted the supplier $S_4$ as the best 'g-resilient' supplier. To investigate application potential of the proposed model; a comparative analysis of the results have been furnished by using Fuzzy-TOPSIS, Fuzzy-VIKOR and Fuzzy-TODIM approaches (alternatives ranking orders have appeared the same). The proposed decision support module has been made to avoid complex dominance measurement formulations (delineated in prospect theory function) as depicted in TODIM. The work carried out herein may support the supply chain managers in order to identify suppliers' ill (poor)-performing areas requiring necessary improvements in future.

A 'dominance-based' novel decision support framework in combination with grey numbers set theory has been proposed (as documented in ***Chapter 5***) for selection of third party logistic (3PL) service providers. Four 3PL service provider alternatives ($A_1$, $A_2$, $A_3$ and $A_4$) have been studied against thirty five 3PL performance evaluation criteria. Alternative 3PL ($A_4$) has been ranked as the best; while, 3PL alternative ($A_3$) has appeared as the worst choice of selection. The said 3PL service provider selection problem has also been solved by the application of grey-TOPSIS approach to find the suitability of the proposed framework in various complex decision making scenario. The result (3PL ranking order) obtained through grey-TOPSIS has been found exactly similar to that of the proposed framework. Hence, it is concluded that the work has contributed/ supported the firm's manager towards the selection of the best 3PL service provider alternative in an effective manner.

In order to evaluate the supply chain's 'ecosilient/ g-resilient' performance index i.e. GRI (as presented in ***Chapter 6***); a fuzzy embedded decision support framework has been developed in conjugation with Fuzzy Set Theory (FST) and Interpretive Structural Modeling (ISM). A set of fourteen supply chain practices (performance criteria/ indices) have been considered as a combination of green and resilient strategy in relation to a case automotive company. The concepts of Fuzzy Performance Importance Index (FPII) accompanied by 'Degree of Similarity' (DOS) adapted from FST have been used to derive the ranking order of various performance criteria. Thus, supply chain performance indicators have been classified into three different performance categories/levels (viz. Regretful, Tolerable, and Satisfactory). Such categorization has been found indeed helpful in view of identifying poor performing areas of supply chain, where further improvement may increase the overall g-resilient index of the company's supply chain. Additionally, in this work, the inter-relationships amongst various g-resilient performance criteria have been developed (in a hierarchical form) by the application of Interpretive Structural Modeling (ISM). The g-resilient index (crisp score) of the case company has been obtained (as $GRI = 0.646$) through the application of the proposed approach. Additionally, the performance indicators viz. $R_7$ (Developing visibility to a clear view of downstream inventories and demand conditions) has appeared as the highest performing criterion; whereas, considerable future improvements for green criterion $G_3$ (ISO 14001 certification) and also for resiliency criterion $R_6$ (Flexible transportation) have been suggested for this particular case company.

In order to evaluate risks associated with e-commerce exercises (as attempted in ***Chapter 7***), an efficient e-commerce risk assessment framework has been provided. The proposed risk assessment framework has been demonstrated through a case empirical illustration for an Indian case company. In this work, total forty-eight risk sources have been recognized and evaluated. The risk extent has been measured in terms of (a) the likelihood of occurrence, and (b) the impact (consequence of risk occurrence). The recognized e-commerce risks have been categorized into five distinct levels (viz. Negligible, Minor, Marginal, Critical and Catastrophic) representing their degree of severity. Top five risk sources (under critical level) viz. R10: Threat of sabotage in internal network; R13: Site or network overload and disruption; R17: Project complexity; R18: Technological newness and R19: Continuous change of system requirements etc. have been identified and the overall ‘crisp risk extent’ (~0.33) has also been determined through the exploration of Fuzzy Inference System (FIS). Finally, an ISM approach has been applied to explore a structural relationship amongst aforementioned five critical risk sources. The relationship developed through the ISM has been found helpful for risk control and possible mitigation towards e-commerce execution in relation to the case company. An appropriate action plan has also been suggested for the concerned company in order to control and, thereby, to reduce possibility of adverse consequence of risks associated with the e-commerce.

## Limitations and Future Scope

The following section articulates limitations of the present work. Scope of future work has also been provided herein.

While analyzing decision support systems (viz. fuzzy-TODIM, fuzzy-TOPSIS etc.) for solving robot selection problems (as documented in ***Chapter 3***), Triangular Fuzzy Numbers (TFNs) have been used to transform linguistic human judgment into appropriate fuzzy scores. The linguistic terms set (and corresponding fuzzy representation) explored herein, has been adapted from the available literature resource. Apart from TFNs there exists trapezoidal, bell-shaped, Gaussian fuzzy numbers (and corresponding membership functions). It is worth of investigating which fuzzy membership function offers the most reliable decision outcome.

In original formulation of traditional TODIM, TODIM is based on crisp weight of the selection attributes and the summation of weights of individual attributes must be equal to 1. However, exact attribute weight (crisp) is very difficult to estimate. Hence, in the work (as described in ***Chapter 3***), the attribute priority weights have been assessed subjectively by the decision making group. Linguistic weight as assigned by the experts has been transformed into appropriate fuzzy numbers and by exploring fuzzy aggregation rule, aggregated fuzzy weights of individual attributes has been obtained. Finally, aggregated fuzzy weights of individual attributes have been defuzzified to obtain equivalent 'crisp' weights. The crisp weights (defuzzified) have been utilized in the fuzzy-TODIM approprach attempted herein. In this case, summation of crisp (defuzzified) weights of different attributes does not come equal to 1.

In course of analyzing decision making problems through fuzzy-TODIM, while comparing partial dominance between two alternatives (with respect to a particular criterion); the crisp (defuzzified) scores corresponding to the ratings of alternatives have been compared in order to check the occurrence of gain or loss. The vertex method of defuzzification has been utilized in this part of work (Refer to ***Chapter 3***). However, to compute the measure of partial dominance, the fuzzy distance measure has been explored. Apart from vertex method, a variety of defuzzification formulae are available in literature; and hence, it is worth of checking the deviation in the final ranking order (if it occurs) due to exploration of different defuzzification modules.

The decision support system to solve robot selection problem (through fuzzy-TODIM) explores the concept of fuzzy 'Degree of Similarity' (DOS) towards evaluating dominance for a pair of alternatives with respect to a particular criterion. Results indicate that the measure of fuzzy degree of similarity could be an effective alternative in place of fuzzy distance measure for measuring dominance between two alternatives. However, in literature, it has been observed that a variety of formulae have been proposed by different authors towards refining the mathematical construct and evaluating the accurate value of similarity measure (between two fuzzy numbers).

The proposed grey-TODIM approach (for industrial robot selection) utilizes crisp weights of the evaluation criteria. Criteria weights must be selected in such a way that the condition $\sum_{j=1}^{n} w_j = 1$ is satisfied. Based on those crisp weights, reference criterion is identified and relative weights of different criteria are determined. In this work (Refer to ***Chapter 3***), values of criteria weight have been presumed. A more logical way to determine criteria weights would be to explore Analytic Hierarchy Process (AHP). Weights can also be assigned by subjective preferences of the Decision-Makers (DMs). Linguistic weights can further be represented by appropriate fuzzy numbers (as in case of standard fuzzy based decision support systems). Aggregated fuzzy priority weights can be defuzzified again to compute crisp weight against individual evaluation criterion. However, in this case, summation of all criteria weights may not be equal to unity.

In relation to the proposed decision support framework for 3PL service provider selection (as reported in ***Chapter 5***), the work may be extended in the following directions:

a) Effect of variation of decision-makers' risk bearing attitude (i.e. optimistic, neutral, pessimistic) on the final decision outcome may be studied in future.
b) Apart from grey numbers set theory, the procedural steps of the proposed 'dominance-based' decision making approach may be formulated by exploring fuzzy set (generalized, interval-valued, and intuitionistic fuzzy sets, vague set) theories.

c) Apart from grey-TOPSIS, grey-TODIM; application potential of the proposed decision support framework may also be compared with other grey based decision making modules like grey relation analysis, grey-MOORA etc.

Additionally, an empirical illustration has been presented in aforesaid work (3PL providers selection) to demonstrate application potential of the proposed 'Dominance-Based' grey decision support system in comparison with grey-TOPSIS. Empirical research is a kind of research using empirical evidences. It is a way of gaining knowledge by means of direct and indirect observation or experiences of others. The practical application of the aforesaid work needs to be explored in future.

In course of assessing supply chain's Ecosilient (G-Resilient) performance (as attempted in ***Chapter 6***); interrelationships amongst various performance indicators have been analyzed through exploration of ISM. The feasibility of the criteria-hierarchy (consolidated list of criteria/attributes) may be reduced in dimension through factor analysis. The entire focus of the proposed 'g-resilient' index is only to assess the g-resilient supply chain performance of a case automotive company. Consequently, the work carried out in this dissertation is limited to that particular case company.

While pursuing risk assessment in e-commerce domain (as attempted in ***Chapter 7***), necessary action requirement plans have been suggested towards effective control and mitigation of critical risks. However, this has just been a proposal not implemented in practice. A comprehensive framework has been proposed in this dissertation to assess and mitigate the risks associated with e-commerce exercises.

In this dissertation, decision support systems for various decision making scenarios have been developed and demonstrated using fuzzy and grey set theories. As metaheuristic and artificial intelligence have huge scope, the decision making practices can be strengthen by using the same.

## Research Contributions

- Improvement of Fuzzy-TODIM through exploration of the concept of fuzzy 'Degree of Similarity' (DOS) through a case empirical robot selection problem.
- Development of grey-TODIM through exploration of grey numbers set theory through a case empirical robot selection problem.
- Development of fuzzy extended PROMETHEE towards solving robot selection problem. The proposed DSS can deal with a combination of objective as well as subjective data, simultaneously.
- Development of a novel fuzzy based decision support framework towards g-resilient supplier selection. Exploration of supplier's 'G-Resilient' performance index has been introduced. Fuzzy Performance Importance Index (FPII) has been used to identify ill (poor)-performing criteria of candidate suppliers. ISM model has depicted interrelationships amongst g-resilient performance indices.
- Development of a novel 'dominance-based' DSS through exploration of the concept of traditional TODIM as well as grey set theory towards selection of 3PL service providers.
- Establishment of a performance evaluation index system for estimating supply chain's 'g-resilient' or 'ecosilient' performance index in relation to a case automotive company.
- Conceptualizing an integrated fuzzy embedded decision support framework towards analyzing e-commerce risks. The overall 'crisp risk extent' has been computed for a particular case company. Critical risk sources have been modeled through ISM approach to reveal their interdependencies /interrelationships in relation to e-commerce exercise

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# APPENDIX A

**Questionnaire for Collecting Expert Opinion towards Assessment of Supply Chain's g-resilient Index**

**NAME:** ……………………………………………………………………… (Optional)

**DESIGNATION:** ……………………………................................................... (Optional)

**NUMBER OF YEARS SERVED THE COMPANY:** ………………………….. (Optional)

[Thanks for your kind cooperation towards helping academic fraternity]

*Be assured that your identity will be kept confidential*

You are requested to put your personal (unbiased) opinion towards evaluating g-resilient (Green+Resilient) index of your company ***(company name will be kept confidential and not be revealed in our report)*** as a case empirical study.

Please use the linguistic terminology (use abbreviations) **(Table A1)** to assign **priority weight** (degree of important) of individual criterion which influences a company's g-resilient performance.

Table A1: Definitions of linguistic variables for assignment of priority weights of criteria (9-member linguistic terms set)

| Linguistic terms (Priority **weights**) | Abbreviation |
|---|---|
| Absolutely Low | (AL) |
| Very Low | (VL) |
| Low | (L) |
| Medium Low | (ML) |
| Medium | (M) |
| Medium High | (MH) |
| High | (H) |
| Very High | (VH) |
| Absolutely High | (AH) |

**Please fill up the table (Table A2)**

Assignment of priority weight against individual criterions (Put **X** mark against your choice) (Refer to **Table A1**)

| G-resilient index | Criteria | Linguistic terms for assigning priority weights | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | AL (Absolutely Low) | VL (Very Low) | L (Low) | ML (Medium Low) | M (Medium) | MH (Medium High) | H (High) | VH (Very High) | AH (Absolutely High) |
| Green behavior | Environmental collaboration with suppliers | | | | | | | | | |
| | Environmental monitoring upon suppliers | | | | | | | | | |
| | ISO 14001 certification | | | | | | | | | |
| | To reduce energy consumption | | | | | | | | | |
| | To reuse/recycling materials and packaging | | | | | | | | | |
| | Environmental collaboration with the customer | | | | | | | | | |
| | Reverse logistics performance | | | | | | | | | |
| Resilient behavior | Sourcing strategies to allow switching of suppliers | | | | | | | | | |
| | Flexible supply base/flexible sourcing | | | | | | | | | |
| | Strategic stock | | | | | | | | | |
| | Lead time reduction | | | | | | | | | |
| | Creating total supply chain visibility | | | | | | | | | |
| | Flexible transportation | | | | | | | | | |
| | Developing visibility to a clear view of downstream inventories and demand conditions | | | | | | | | | |

Please use the linguistic terminology (use abbreviations) **(Table A3)** to assign **performance rating** (the degree/extent up to which your company is performing in that particular aspect) of individual criterion which determines a company's g-resilient performance index.

Table A3: Definitions of linguistic variables for criteria ratings (performance extent) (9-member linguistic terms set)

| Linguistic terms (Attribute/criteria **ratings**) | Abbreviation |
|---|---|
| Absolutely Poor | (AP) |
| Very Poor | (VP) |
| Poor | (P) |
| Medium Poor | (MP) |
| Medium | (M) |
| Medium Good | (MG) |
| Good | (G) |
| Very Good | (VG) |
| Absolutely Good | (AG) |

**Please fill up the table (Table A4)**

Assignment of performance rating against individual criterions (Put **X** mark against your choice) (Refer to **Table A3**)

| G-resilient index | Criteria | Linguistic terms for assigning performance ratings | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | AP (Absolutely Poor) | VP (Very Poor) | P (Poor) | MP (Medium Poor) | M (Medium) | MG (Medium Good) | G (Good) | VG (Very Good) | AG (Absolutely Good) |
| Green behavior | Environmental collaboration with suppliers | | | | | | | | | |
| | Environmental monitoring upon suppliers | | | | | | | | | |
| | ISO 14001 certification | | | | | | | | | |
| | To reduce energy consumption | | | | | | | | | |
| | To reuse/recycling materials and packaging | | | | | | | | | |
| | Environmental collaboration with the customer | | | | | | | | | |
| | Reverse logistics performance | | | | | | | | | |
| Resilient behavior | Sourcing strategies to allow switching of suppliers | | | | | | | | | |
| | Flexible supply base/flexible sourcing | | | | | | | | | |
| | Strategic stock | | | | | | | | | |
| | Lead time reduction | | | | | | | | | |
| | Creating total supply chain visibility | | | | | | | | | |
| | Flexible transportation | | | | | | | | | |
| | Developing visibility to a clear view of downstream inventories and demand conditions | | | | | | | | | |

*THANKS for your kind cooperation*

# APPENDIX B

**Questionnaire for Collecting Expert Opinion towards E-Commerce Risks**

**NAME:** ……………………………………………………………………… (Optional)

**DESIGNATION:** ……………………………................................................... (Optional)

**NUMBER OF YEARS SERVED THE COMPANY:** ………………………….. (Optional)

[Thanks for your kind cooperation towards helping academic fraternity]

*Be assured that your identity will be kept confidential*

$RISK = \textbf{\textit{Likelihood (probability) of occurrence}} \times \textbf{\textit{impact}}$

You are requested to put your personal (unbiased) opinion towards evaluating E-commence risk of your company ***(company name will be kept confidential and not be revealed in our report)*** as a case empirical study.

Please use the linguistic terminology (use abbreviations) **(Table B1)** to assign **likelihood (probability) of occurrence** (i.e. how frequent these are expected to incur) of individual risk sources which influence a company's overall E-commerce risk.

Table B1: Definitions of linguistic variables for assignment of **likelihood of occurrence** of different risk sources (A-7 member linguistic terms set)

| Linguistic terms<br>(**likelihood of occurrence**) | Abbreviation |
|---|---|
| Absolutely Rare | AR |
| Very Rare | VR |
| Rare | R |
| Often | O |
| Frequent | F |
| Very Frequent | VF |
| Highly Frequent | HF |

**<u>Please fill up the following table (Table B2)</u>**

Assignment of **<u>likelihood of occurrence</u>** against individual risk sources (Put **<u>X</u>** mark against your choice) (Refer to **Table B1**)

Please use the linguistic terminology (use abbreviations) to assign **<u>likelihood of occurrence</u>** of individual risk sources in relation to the company's overall e-commerce risk.

| **Potential risk sources** | **Linguistic terms for assigning <u>likelihood of occurrence</u>** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **AR (Absolutely Rare)** | **VR (Very Rare)** | **R (Rare)** | **O (Often)** | **F (Frequent)** | **VF (Very Frequent)** | **HF (Highly Frequent)** |
| Hacker gaining unauthorized access | | | | | | | |
| Absence of firewall | | | | | | | |
| Lack of using cryptography | | | | | | | |
| Poor "key" management | | | | | | | |
| Malicious code attacks | | | | | | | |
| Disclosure of sensitive information | | | | | | | |
| Loss of audit trail | | | | | | | |
| Natural disaster-caused equipment failure | | | | | | | |
| Human factor-caused equipment failure | | | | | | | |
| Threat of sabotage in internal network | | | | | | | |
| Inadequate backup systems | | | | | | | |
| Software or hardware problem-caused failure system | | | | | | | |
| Site or network overload and disruption | | | | | | | |
| Poor design, code or maintenance procedure | | | | | | | |
| Wrong functions and properties development | | | | | | | |
| Wrong user inference development | | | | | | | |
| Project complexity | | | | | | | |
| Technological newness | | | | | | | |
| Continuous change of system requirements | | | | | | | |
| Wrong schedule estimation | | | | | | | |

| Potential risk sources | Linguistic terms for assigning likelihood of occurrence | | | | | | |
|---|---|---|---|---|---|---|---|
| | AR (Absolutely Rare) | VR (Very Rare) | R (Rare) | O (Often) | F (Frequent) | VF (Very Frequent) | HF (Highly Frequent) |
| Project behind schedule | | | | | | | |
| Project over budget | | | | | | | |
| Inadequate cash flow | | | | | | | |
| Personnel shortfalls | | | | | | | |
| Lack of expertise and experience in E-commerce | | | | | | | |
| Loss of key person | | | | | | | |
| Lack of top management support | | | | | | | |
| Poor project planning | | | | | | | |
| Loss of control over vendor | | | | | | | |
| Indefinite project scope | | | | | | | |
| Lack of contingency plans | | | | | | | |
| Business process redesign | | | | | | | |
| Organizational restructuring | | | | | | | |
| Lack of trust between your organization and merchant or customer | | | | | | | |
| Inappropriate media for the product or service | | | | | | | |
| Lack of international legal standards | | | | | | | |
| New laws, regulations, and judicial decisions constantly change the online legal landscape | | | | | | | |
| Uncertain legal jurisdiction | | | | | | | |
| Incompletion of contract terms | | | | | | | |
| Loss of data control | | | | | | | |
| Loss of control over information technology | | | | | | | |
| Hidden cost | | | | | | | |
| Unclear project objectives | | | | | | | |
| Lack of vendor expertise and experience | | | | | | | |
| Lock-in situation | | | | | | | |
| Vendor offers outdated technology skill | | | | | | | |
| Different users with difference in culture customers and business styles | | | | | | | |
| Language barrier | | | | | | | |

Please use the linguistic terminology (use abbreviations) **(Table B3)** to assign **impact of risk (consequence of exposure)** i.e. the intensity of impact imposed due to occurrence of adverse event (risk).

Table B3: Definitions of linguistic variables for assignment of **impact** of different risk sources (A-7 member linguistic terms set)

| Linguistic terms (**impact of risk occurrence**) | Abbreviation |
|---|---|
| Absolutely Low | AL |
| Very Low | VL |
| Low | L |
| Moderate | M |
| Serious | S |
| Critical | C |
| Highly Critical | HC |

**Please fill up the table (Table B4)**

Assignment of **impact** against individual risk sources (Put **X** mark against your choice) (Refer to **Table B3**)

Please use the linguistic terminology (use abbreviations) to assign **impact** of individual risk sources in relation to the company's overall e-commerce risk.

| **Potential risk sources** | **Linguistic terms for assigning impact** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **AL (Absolutely Low)** | **VL (Very Low)** | **L (Low)** | **M (Moderate)** | **S (Serious)** | **C (Critical)** | **HC (Highly Critical)** |
| Hacker gaining unauthorized access | | | | | | | |
| Absence of firewall | | | | | | | |
| Lack of using cryptography | | | | | | | |
| Poor "key" management | | | | | | | |
| Malicious code attacks | | | | | | | |
| Disclosure of sensitive information | | | | | | | |
| Loss of audit trail | | | | | | | |
| Natural disaster-caused equipment failure | | | | | | | |
| Human factor-caused equipment failure | | | | | | | |
| Threat of sabotage in internal network | | | | | | | |
| Inadequate backup systems | | | | | | | |
| Software or hardware problem-caused failure system | | | | | | | |
| Site or network overload and disruption | | | | | | | |
| Poor design, code or maintenance procedure | | | | | | | |
| Wrong functions and properties development | | | | | | | |
| Wrong user inference development | | | | | | | |
| Project complexity | | | | | | | |
| Technological newness | | | | | | | |
| Continuous change of system requirements | | | | | | | |
| Wrong schedule estimation | | | | | | | |

| Potential risk sources | **Linguistic terms for assigning impact** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **AL (Absolutely Low)** | **VL (Very Low)** | **L (Low)** | **M (Moderate)** | **S (Serious)** | **C (Critical)** | **HC (Highly Critical)** |
| Project behind schedule | | | | | | | |
| Project over budget | | | | | | | |
| Inadequate cash flow | | | | | | | |
| Personnel shortfalls | | | | | | | |
| Lack of expertise and experience in E-commerce | | | | | | | |
| Loss of key person | | | | | | | |
| Lack of top management support | | | | | | | |
| Poor project planning | | | | | | | |
| Loss of control over vendor | | | | | | | |
| Indefinite project scope | | | | | | | |
| Lack of contingency plans | | | | | | | |
| Business process redesign | | | | | | | |
| Organizational restructuring | | | | | | | |
| Lack of trust between your organization and merchant or customer | | | | | | | |
| Inappropriate media for the product or service | | | | | | | |
| Lack of international legal standards | | | | | | | |
| New laws, regulations, and judicial decisions constantly change the online legal landscape | | | | | | | |
| Uncertain legal jurisdiction | | | | | | | |
| Incompletion of contract terms | | | | | | | |
| Loss of data control | | | | | | | |
| Loss of control over information technology | | | | | | | |
| Hidden cost | | | | | | | |
| Unclear project objectives | | | | | | | |
| Lack of vendor expertise and experience | | | | | | | |
| Lock-in situation | | | | | | | |
| Vendor offers outdated technology skill | | | | | | | |
| Different users with difference in culture customers and business styles | | | | | | | |
| Language barrier | | | | | | | |

*THANKS for your kind cooperation*

# APPENDIX C

## Fuzzy Rule Base

| Rule No. | IF | | | | | THEN |
|---|---|---|---|---|---|---|
| | R9 | R13 | R18 | R19 | R47 | Overall Risk Extent |
| 1 | Tolerant (T) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Less Tolerant (LT) |
| 2 | Tolerant (T) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Moderate (M) | Less Tolerant (LT) |
| 3 | Tolerant (T) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Extreme (E) | Tolerant (T) |
| 4 | Tolerant (T) | Tolerant (T) | Tolerant (T) | Moderate (M) | Tolerant (T) | Less Tolerant (LT) |
| 5 | Tolerant (T) | Tolerant (T) | Tolerant (T) | Moderate (M) | Moderate (M) | Less Tolerant (LT) |
| 6 | Tolerant (T) | Tolerant (T) | Tolerant (T) | Moderate (M) | Extreme (E) | Tolerant (T) |
| 7 | Tolerant (T) | Tolerant (T) | Tolerant (T) | Extreme (E) | Tolerant (T) | Less Tolerant (LT) |
| 8 | Tolerant (T) | Tolerant (T) | Tolerant (T) | Extreme (E) | Moderate (M) | Tolerant (T) |
| 9 | Tolerant (T) | Tolerant (T) | Tolerant (T) | Extreme (E) | Extreme (E) | Tolerant (T) |
| 10 | Tolerant (T) | Tolerant (T) | Moderate (M) | Tolerant (T) | Tolerant (T) | Less Tolerant (LT) |
| 11 | Tolerant (T) | Tolerant (T) | Moderate (M) | Tolerant (T) | Moderate (M) | Less Tolerant (LT) |
| 12 | Tolerant (T) | Tolerant (T) | Moderate (M) | Tolerant (T) | Extreme (E) | Tolerant (T) |
| 13 | Tolerant (T) | Tolerant (T) | Moderate (M) | Moderate (M) | Tolerant (T) | Less Tolerant (LT) |
| 14 | Tolerant (T) | Tolerant (T) | Moderate (M) | Moderate (M) | Moderate (M) | Less Tolerant (LT) |
| 15 | Tolerant (T) | Tolerant (T) | Moderate (M) | Moderate (M) | Extreme (E) | Tolerant (T) |
| 16 | Tolerant (T) | Tolerant (T) | Moderate (M) | Extreme (E) | Tolerant (T) | Less Tolerant (LT) |
| 17 | Tolerant (T) | Tolerant (T) | Moderate (M) | Extreme (E) | Moderate (M) | Tolerant (T) |
| 18 | Tolerant (T) | Tolerant (T) | Moderate (M) | Extreme (E) | Extreme (E) | Tolerant (T) |
| 19 | Tolerant (T) | Tolerant (T) | Extreme (E) | Tolerant (T) | Tolerant (T) | Less Tolerant (LT) |
| 20 | Tolerant (T) | Tolerant (T) | Extreme (E) | Tolerant (T) | Moderate (M) | Less Tolerant (LT) |
| 21 | Tolerant (T) | Tolerant (T) | Extreme (E) | Tolerant (T) | Extreme (E) | Tolerant (T) |
| 22 | Tolerant (T) | Tolerant (T) | Extreme (E) | Moderate (M) | Tolerant (T) | Less Tolerant (LT) |
| 23 | Tolerant (T) | Tolerant (T) | Extreme (E) | Moderate (M) | Moderate (M) | Less Tolerant (LT) |
| 24 | Tolerant (T) | Tolerant (T) | Extreme (E) | Moderate (M) | Extreme (E) | Tolerant (T) |
| 25 | Tolerant (T) | Tolerant (T) | Extreme (E) | Extreme (E) | Tolerant (T) | Less Tolerant (LT) |
| 26 | Tolerant (T) | Tolerant (T) | Extreme (E) | Extreme (E) | Moderate (M) | Tolerant (T) |
| 27 | Tolerant (T) | Tolerant (T) | Extreme (E) | Extreme (E) | Extreme (E) | Tolerant (T) |
| 28 | Tolerant (T) | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Less Tolerant (LT) |
| 29 | Tolerant (T) | Moderate (M) | Tolerant (T) | Tolerant (T) | Moderate (M) | Tolerant (T) |
| 30 | Tolerant (T) | Moderate (M) | Tolerant (T) | Tolerant (T) | Extreme (E) | Tolerant (T) |
| 31 | Tolerant (T) | Moderate (M) | Tolerant (T) | Moderate (M) | Tolerant (T) | Less Tolerant (LT) |
| 32 | Tolerant (T) | Moderate (M) | Tolerant (T) | Moderate (M) | Moderate (M) | Tolerant (T) |
| 33 | Tolerant (T) | Moderate (M) | Tolerant (T) | Moderate (M) | Extreme (E) | Moderate (M) |
| 34 | Tolerant (T) | Moderate (M) | Tolerant (T) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 35 | Tolerant (T) | Moderate (M) | Tolerant (T) | Extreme (E) | Moderate (M) | Tolerant (T) |

| Rule No. | IF | | | | | THEN |
|---|---|---|---|---|---|---|
| | R9 | R13 | R18 | R19 | R47 | Overall Risk Extent |
| 36 | Tolerant (T) | Moderate (M) | Tolerant (T) | Extreme (E) | Extreme (E) | Moderate (M) |
| 37 | Tolerant (T) | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 38 | Tolerant (T) | Moderate (M) | Moderate (M) | Tolerant (T) | Moderate (M) | Tolerant (T) |
| 39 | Tolerant (T) | Moderate (M) | Moderate (M) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 40 | Tolerant (T) | Moderate (M) | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 41 | Tolerant (T) | Moderate (M) | Moderate (M) | Moderate (M) | Moderate (M) | Tolerant (T) |
| 42 | Tolerant (T) | Moderate (M) | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) |
| 43 | Tolerant (T) | Moderate (M) | Moderate (M) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 44 | Tolerant (T) | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) | Tolerant (T) |
| 45 | Tolerant (T) | Moderate (M) | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) |
| 46 | Tolerant (T) | Moderate (M) | Extreme (E) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 47 | Tolerant (T) | Moderate (M) | Extreme (E) | Tolerant (T) | Moderate (M) | Tolerant (T) |
| 48 | Tolerant (T) | Moderate (M) | Extreme (E) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 49 | Tolerant (T) | Moderate (M) | Extreme (E) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 50 | Tolerant (T) | Moderate (M) | Extreme (E) | Moderate (M) | Moderate (M) | Tolerant (T) |
| 51 | Tolerant (T) | Moderate (M) | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) |
| 52 | Tolerant (T) | Moderate (M) | Extreme (E) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 53 | Tolerant (T) | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) | Tolerant (T) |
| 54 | Tolerant (T) | Moderate (M) | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) |
| 55 | Tolerant (T) | Extreme (E) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 56 | Tolerant (T) | Extreme (E) | Tolerant (T) | Tolerant (T) | Moderate (M) | Tolerant (T) |
| 57 | Tolerant (T) | Extreme (E) | Tolerant (T) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 58 | Tolerant (T) | Extreme (E) | Tolerant (T) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 59 | Tolerant (T) | Extreme (E) | Tolerant (T) | Moderate (M) | Moderate (M) | Tolerant (T) |
| 60 | Tolerant (T) | Extreme (E) | Tolerant (T) | Moderate (M) | Extreme (E) | Moderate (M) |
| 61 | Tolerant (T) | Extreme (E) | Tolerant (T) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 62 | Tolerant (T) | Extreme (E) | Tolerant (T) | Extreme (E) | Moderate (M) | Moderate (M) |
| 63 | Tolerant (T) | Extreme (E) | Tolerant (T) | Extreme (E) | Extreme (E) | Moderate (M) |
| 64 | Tolerant (T) | Extreme (E) | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 65 | Tolerant (T) | Extreme (E) | Moderate (M) | Tolerant (T) | Moderate (M) | Moderate (M) |
| 66 | Tolerant (T) | Extreme (E) | Moderate (M) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 67 | Tolerant (T) | Extreme (E) | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 68 | Tolerant (T) | Extreme (E) | Moderate (M) | Moderate (M) | Moderate (M) | Moderate (M) |
| 69 | Tolerant (T) | Extreme (E) | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) |
| 70 | Tolerant (T) | Extreme (E) | Moderate (M) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 71 | Tolerant (T) | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) | Tolerant (T) |
| 72 | Tolerant (T) | Extreme (E) | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) |
| 73 | Tolerant (T) | Extreme (E) | Extreme (E) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 74 | Tolerant (T) | Extreme (E) | Extreme (E) | Tolerant (T) | Moderate (M) | Moderate (M) |

| Rule No. | IF | | | | | THEN |
|---|---|---|---|---|---|---|
| | R9 | R13 | R18 | R19 | R47 | Overall Risk Extent |
| 75 | Tolerant (T) | Extreme (E) | Extreme (E) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 76 | Tolerant (T) | Extreme (E) | Extreme (E) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 77 | Tolerant (T) | Extreme (E) | Extreme (E) | Moderate (M) | Moderate (M) | Moderate (M) |
| 78 | Tolerant (T) | Extreme (E) | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) |
| 79 | Tolerant (T) | Extreme (E) | Extreme (E) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 80 | Tolerant (T) | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) | Moderate (M) |
| 81 | Tolerant (T) | Extreme (E) | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) |
| 82 | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 83 | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Moderate (M) | Tolerant (T) |
| 84 | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 85 | Moderate (M) | Tolerant (T) | Tolerant (T) | Moderate (M) | Tolerant (T) | Less Tolerant (LT) |
| 86 | Moderate (M) | Tolerant (T) | Tolerant (T) | Moderate (M) | Moderate (M) | Tolerant (T) |
| 87 | Moderate (M) | Tolerant (T) | Tolerant (T) | Moderate (M) | Extreme (E) | Moderate (M) |
| 88 | Moderate (M) | Tolerant (T) | Tolerant (T) | Extreme (E) | Tolerant (T) | Less Tolerant (LT) |
| 89 | Moderate (M) | Tolerant (T) | Tolerant (T) | Extreme (E) | Moderate (M) | Tolerant (T) |
| 90 | Moderate (M) | Tolerant (T) | Tolerant (T) | Extreme (E) | Extreme (E) | Moderate (M) |
| 91 | Moderate (M) | Tolerant (T) | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 92 | Moderate (M) | Tolerant (T) | Moderate (M) | Tolerant (T) | Moderate (M) | Tolerant (T) |
| 93 | Moderate (M) | Tolerant (T) | Moderate (M) | Tolerant (T) | Extreme (E) | Tolerant (T) |
| 94 | Moderate (M) | Tolerant (T) | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 95 | Moderate (M) | Tolerant (T) | Moderate (M) | Moderate (M) | Moderate (M) | Tolerant (T) |
| 96 | Moderate (M) | Tolerant (T) | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) |
| 97 | Moderate (M) | Tolerant (T) | Moderate (M) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 98 | Moderate (M) | Tolerant (T) | Moderate (M) | Extreme (E) | Moderate (M) | Moderate (M) |
| 99 | Moderate (M) | Tolerant (T) | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) |
| 100 | Moderate (M) | Tolerant (T) | Extreme (E) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 101 | Moderate (M) | Tolerant (T) | Extreme (E) | Tolerant (T) | Moderate (M) | Tolerant (T) |
| 102 | Moderate (M) | Tolerant (T) | Extreme (E) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 103 | Moderate (M) | Tolerant (T) | Extreme (E) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 104 | Moderate (M) | Tolerant (T) | Extreme (E) | Moderate (M) | Moderate (M) | Tolerant (T) |
| 105 | Moderate (M) | Tolerant (T) | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) |
| 106 | Moderate (M) | Tolerant (T) | Extreme (E) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 107 | Moderate (M) | Tolerant (T) | Extreme (E) | Extreme (E) | Moderate (M) | Moderate (M) |
| 108 | Moderate (M) | Tolerant (T) | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) |
| 109 | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 110 | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) | Moderate (M) | Moderate (M) |
| 111 | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 112 | Moderate (M) | Moderate (M) | Tolerant (T) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 113 | Moderate (M) | Moderate (M) | Tolerant (T) | Moderate (M) | Moderate (M) | Moderate (M) |

| Rule No. | IF | | | | | THEN |
|---|---|---|---|---|---|---|
| | R9 | R13 | R18 | R19 | R47 | Overall Risk Extent |
| 114 | Moderate (M) | Moderate (M) | Tolerant (T) | Moderate (M) | Extreme (E) | Moderate (M) |
| 115 | Moderate (M) | Moderate (M) | Tolerant (T) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 116 | Moderate (M) | Moderate (M) | Tolerant (T) | Extreme (E) | Moderate (M) | Tolerant (T) |
| 117 | Moderate (M) | Moderate (M) | Tolerant (T) | Extreme (E) | Extreme (E) | Moderate (M) |
| 118 | Moderate (M) | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 119 | Moderate (M) | Moderate (M) | Moderate (M) | Tolerant (T) | Moderate (M) | Tolerant (T) |
| 120 | Moderate (M) | Moderate (M) | Moderate (M) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 121 | Moderate (M) | Moderate (M) | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 122 | Moderate (M) | Moderate (M) | Moderate (M) | Moderate (M) | Moderate (M) | Tolerant (T) |
| 123 | Moderate (M) | Moderate (M) | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) |
| 124 | Moderate (M) | Moderate (M) | Moderate (M) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 125 | Moderate (M) | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) | Moderate (M) |
| 126 | Moderate (M) | Moderate (M) | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) |
| 127 | Moderate (M) | Moderate (M) | Extreme (E) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 128 | Moderate (M) | Moderate (M) | Extreme (E) | Tolerant (T) | Moderate (M) | Tolerant (T) |
| 129 | Moderate (M) | Moderate (M) | Extreme (E) | Tolerant (T) | Extreme (E) | Tolerant (T) |
| 130 | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 131 | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) | Moderate (M) | Tolerant (T) |
| 132 | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) |
| 133 | Moderate (M) | Moderate (M) | Extreme (E) | Extreme (E) | Tolerant (T) | Tolerant (T) |
| 134 | Moderate (M) | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) | Moderate (M) |
| 135 | Moderate (M) | Moderate (M) | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) |
| 136 | Moderate (M) | Extreme (E) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Moderate (M) |
| 137 | Moderate (M) | Extreme (E) | Tolerant (T) | Tolerant (T) | Moderate (M) | Moderate (M) |
| 138 | Moderate (M) | Extreme (E) | Tolerant (T) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 139 | Moderate (M) | Extreme (E) | Tolerant (T) | Moderate (M) | Tolerant (T) | Moderate (M) |
| 140 | Moderate (M) | Extreme (E) | Tolerant (T) | Moderate (M) | Moderate (M) | Moderate (M) |
| 141 | Moderate (M) | Extreme (E) | Tolerant (T) | Moderate (M) | Extreme (E) | Extreme (E) |
| 142 | Moderate (M) | Extreme (E) | Tolerant (T) | Extreme (E) | Tolerant (T) | Moderate (M) |
| 143 | Moderate (M) | Extreme (E) | Tolerant (T) | Extreme (E) | Moderate (M) | Moderate (M) |
| 144 | Moderate (M) | Extreme (E) | Tolerant (T) | Extreme (E) | Extreme (E) | Extreme (E) |
| 145 | Moderate (M) | Extreme (E) | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) |
| 146 | Moderate (M) | Extreme (E) | Moderate (M) | Tolerant (T) | Moderate (M) | Moderate (M) |
| 147 | Moderate (M) | Extreme (E) | Moderate (M) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 148 | Moderate (M) | Extreme (E) | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) |
| 149 | Moderate (M) | Extreme (E) | Moderate (M) | Moderate (M) | Moderate (M) | Moderate (M) |
| 150 | Moderate (M) | Extreme (E) | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) |
| 151 | Moderate (M) | Extreme (E) | Moderate (M) | Extreme (E) | Tolerant (T) | Moderate (M) |
| 152 | Moderate (M) | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) | Moderate (M) |

| Rule No. | IF | | | | | THEN |
|---|---|---|---|---|---|---|
| | R9 | R13 | R18 | R19 | R47 | Overall Risk Extent |
| 153 | Moderate (M) | Extreme (E) | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) |
| 154 | Moderate (M) | Extreme (E) | Extreme (E) | Tolerant (T) | Tolerant (T) | Moderate (M) |
| 155 | Moderate (M) | Extreme (E) | Extreme (E) | Tolerant (T) | Moderate (M) | Moderate (M) |
| 156 | Moderate (M) | Extreme (E) | Extreme (E) | Tolerant (T) | Extreme (E) | Moderate (M) |
| 157 | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) | Tolerant (T) | Moderate (M) |
| 158 | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) | Moderate (M) | Moderate (M) |
| 159 | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) |
| 160 | Moderate (M) | Extreme (E) | Extreme (E) | Extreme (E) | Tolerant (T) | Moderate (M) |
| 161 | Moderate (M) | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) | Moderate (M) |
| 162 | Moderate (M) | Extreme (E) | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) |
| 163 | Extreme (E) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Moderate (M) |
| 164 | Extreme (E) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Moderate (M) | Moderate (M) |
| 165 | Extreme (E) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Extreme (E) | Extreme (E) |
| 166 | Extreme (E) | Tolerant (T) | Tolerant (T) | Moderate (M) | Tolerant (T) | Moderate (M) |
| 167 | Extreme (E) | Tolerant (T) | Tolerant (T) | Moderate (M) | Moderate (M) | Moderate (M) |
| 168 | Extreme (E) | Tolerant (T) | Tolerant (T) | Moderate (M) | Extreme (E) | Extreme (E) |
| 169 | Extreme (E) | Tolerant (T) | Tolerant (T) | Extreme (E) | Tolerant (T) | Moderate (M) |
| 170 | Extreme (E) | Tolerant (T) | Tolerant (T) | Extreme (E) | Moderate (M) | Moderate (M) |
| 171 | Extreme (E) | Tolerant (T) | Tolerant (T) | Extreme (E) | Extreme (E) | Extreme (E) |
| 172 | Extreme (E) | Tolerant (T) | Moderate (M) | Tolerant (T) | Tolerant (T) | Moderate (M) |
| 173 | Extreme (E) | Tolerant (T) | Moderate (M) | Tolerant (T) | Moderate (M) | Moderate (M) |
| 174 | Extreme (E) | Tolerant (T) | Moderate (M) | Tolerant (T) | Extreme (E) | Extreme (E) |
| 175 | Extreme (E) | Tolerant (T) | Moderate (M) | Moderate (M) | Tolerant (T) | Moderate (M) |
| 176 | Extreme (E) | Tolerant (T) | Moderate (M) | Moderate (M) | Moderate (M) | Moderate (M) |
| 177 | Extreme (E) | Tolerant (T) | Moderate (M) | Moderate (M) | Extreme (E) | Extreme (E) |
| 178 | Extreme (E) | Tolerant (T) | Moderate (M) | Extreme (E) | Tolerant (T) | Moderate (M) |
| 179 | Extreme (E) | Tolerant (T) | Moderate (M) | Extreme (E) | Moderate (M) | Moderate (M) |
| 180 | Extreme (E) | Tolerant (T) | Moderate (M) | Extreme (E) | Extreme (E) | Extreme (E) |
| 181 | Extreme (E) | Tolerant (T) | Extreme (E) | Tolerant (T) | Tolerant (T) | Moderate (M) |
| 182 | Extreme (E) | Tolerant (T) | Extreme (E) | Tolerant (T) | Moderate (M) | Moderate (M) |
| 183 | Extreme (E) | Tolerant (T) | Extreme (E) | Tolerant (T) | Extreme (E) | Extreme (E) |
| 184 | Extreme (E) | Tolerant (T) | Extreme (E) | Moderate (M) | Tolerant (T) | Moderate (M) |
| 185 | Extreme (E) | Tolerant (T) | Extreme (E) | Moderate (M) | Moderate (M) | Moderate (M) |
| 186 | Extreme (E) | Tolerant (T) | Extreme (E) | Moderate (M) | Extreme (E) | Extreme (E) |
| 187 | Extreme (E) | Tolerant (T) | Extreme (E) | Extreme (E) | Tolerant (T) | Moderate (M) |
| 188 | Extreme (E) | Tolerant (T) | Extreme (E) | Extreme (E) | Moderate (M) | Extreme (E) |
| 189 | Extreme (E) | Tolerant (T) | Extreme (E) | Extreme (E) | Extreme (E) | Extreme (E) |
| 190 | Extreme (E) | Moderate (M) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Moderate (M) |
| 191 | Extreme (E) | Moderate (M) | Tolerant (T) | Tolerant (T) | Moderate (M) | Moderate (M) |

| Rule No. | IF | | | | | THEN |
|---|---|---|---|---|---|---|
| | R9 | R13 | R18 | R19 | R47 | Overall Risk Extent |
| 192 | Extreme (E) | Moderate (M) | Tolerant (T) | Tolerant (T) | Extreme (E) | Extreme (E) |
| 193 | Extreme (E) | Moderate (M) | Tolerant (T) | Moderate (M) | Tolerant (T) | Moderate (M) |
| 194 | Extreme (E) | Moderate (M) | Tolerant (T) | Moderate (M) | Moderate (M) | Moderate (M) |
| 195 | Extreme (E) | Moderate (M) | Tolerant (T) | Moderate (M) | Extreme (E) | Extreme (E) |
| 196 | Extreme (E) | Moderate (M) | Tolerant (T) | Extreme (E) | Tolerant (T) | Moderate (M) |
| 197 | Extreme (E) | Moderate (M) | Tolerant (T) | Extreme (E) | Moderate (M) | Extreme (E) |
| 198 | Extreme (E) | Moderate (M) | Tolerant (T) | Extreme (E) | Extreme (E) | Extreme (E) |
| 199 | Extreme (E) | Moderate (M) | Moderate (M) | Tolerant (T) | Tolerant (T) | Moderate (M) |
| 200 | Extreme (E) | Moderate (M) | Moderate (M) | Tolerant (T) | Moderate (M) | Extreme (E) |
| 201 | Extreme (E) | Moderate (M) | Moderate (M) | Tolerant (T) | Extreme (E) | Extreme (E) |
| 202 | Extreme (E) | Moderate (M) | Moderate (M) | Moderate (M) | Tolerant (T) | Moderate (M) |
| 203 | Extreme (E) | Moderate (M) | Moderate (M) | Moderate (M) | Moderate (M) | Extreme (E) |
| 204 | Extreme (E) | Moderate (M) | Moderate (M) | Moderate (M) | Extreme (E) | Extreme (E) |
| 205 | Extreme (E) | Moderate (M) | Moderate (M) | Extreme (E) | Tolerant (T) | Extreme (E) |
| 206 | Extreme (E) | Moderate (M) | Moderate (M) | Extreme (E) | Moderate (M) | Extreme (E) |
| 207 | Extreme (E) | Moderate (M) | Moderate (M) | Extreme (E) | Extreme (E) | Extreme (E) |
| 208 | Extreme (E) | Moderate (M) | Extreme (E) | Tolerant (T) | Tolerant (T) | Extreme (E) |
| 209 | Extreme (E) | Moderate (M) | Extreme (E) | Tolerant (T) | Moderate (M) | Extreme (E) |
| 210 | Extreme (E) | Moderate (M) | Extreme (E) | Tolerant (T) | Extreme (E) | Extreme (E) |
| 211 | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) | Tolerant (T) | Extreme (E) |
| 212 | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) | Moderate (M) | Extreme (E) |
| 213 | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) | Extreme (E) | Extreme (E) |
| 214 | Extreme (E) | Moderate (M) | Extreme (E) | Extreme (E) | Tolerant (T) | Extreme (E) |
| 215 | Extreme (E) | Moderate (M) | Extreme (E) | Extreme (E) | Moderate (M) | Extreme (E) |
| 216 | Extreme (E) | Moderate (M) | Extreme (E) | Extreme (E) | Extreme (E) | Extreme (E) |
| 217 | Extreme (E) | Extreme (E) | Tolerant (T) | Tolerant (T) | Tolerant (T) | Extreme (E) |
| 218 | Extreme (E) | Extreme (E) | Tolerant (T) | Tolerant (T) | Moderate (M) | Extreme (E) |
| 219 | Extreme (E) | Extreme (E) | Tolerant (T) | Tolerant (T) | Extreme (E) | Extreme (E) |
| 220 | Extreme (E) | Extreme (E) | Tolerant (T) | Moderate (M) | Tolerant (T) | Extreme (E) |
| 221 | Extreme (E) | Extreme (E) | Tolerant (T) | Moderate (M) | Moderate (M) | Extreme (E) |
| 222 | Extreme (E) | Extreme (E) | Tolerant (T) | Moderate (M) | Extreme (E) | Absolutely Extreme (AE) |
| 223 | Extreme (E) | Extreme (E) | Tolerant (T) | Extreme (E) | Tolerant (T) | Extreme (E) |
| 224 | Extreme (E) | Extreme (E) | Tolerant (T) | Extreme (E) | Moderate (M) | Extreme (E) |
| 225 | Extreme (E) | Extreme (E) | Tolerant (T) | Extreme (E) | Extreme (E) | Absolutely Extreme (AE) |
| 226 | Extreme (E) | Extreme (E) | Moderate (M) | Tolerant (T) | Tolerant (T) | Extreme (E) |
| 227 | Extreme (E) | Extreme (E) | Moderate (M) | Tolerant (T) | Moderate (M) | Extreme (E) |
| 228 | Extreme (E) | Extreme (E) | Moderate (M) | Tolerant (T) | Extreme (E) | Absolutely Extreme (AE) |
| 229 | Extreme (E) | Extreme (E) | Moderate (M) | Moderate (M) | Tolerant (T) | Extreme (E) |
| 230 | Extreme (E) | Extreme (E) | Moderate (M) | Moderate (M) | Moderate (M) | Extreme (E) |

| Rule No. | IF | | | | | THEN |
|---|---|---|---|---|---|---|
| | R9 | R13 | R18 | R19 | R47 | Overall Risk Extent |
| 231 | Extreme (E) | Extreme (E) | Moderate (M) | Moderate (M) | Extreme (E) | Absolutely Extreme (AE) |
| 232 | Extreme (E) | Extreme (E) | Moderate (M) | Extreme (E) | Tolerant (T) | Extreme (E) |
| 233 | Extreme (E) | Extreme (E) | Moderate (M) | Extreme (E) | Moderate (M) | Absolutely Extreme (AE) |
| 234 | Extreme (E) | Extreme (E) | Moderate (M) | Extreme (E) | Extreme (E) | Absolutely Extreme (AE) |
| 235 | Extreme (E) | Extreme (E) | Extreme (E) | Tolerant (T) | Tolerant (T) | Extreme (E) |
| 236 | Extreme (E) | Extreme (E) | Extreme (E) | Tolerant (T) | Moderate (M) | Absolutely Extreme (AE) |
| 237 | Extreme (E) | Extreme (E) | Extreme (E) | Tolerant (T) | Extreme (E) | Absolutely Extreme (AE) |
| 238 | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) | Tolerant (T) | Extreme (E) |
| 239 | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) | Moderate (M) | Absolutely Extreme (AE) |
| 240 | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) | Extreme (E) | Absolutely Extreme (AE) |
| 241 | Extreme (E) | Extreme (E) | Extreme (E) | Extreme (E) | Tolerant (T) | Extreme (E) |
| 242 | Extreme (E) | Extreme (E) | Extreme (E) | Extreme (E) | Moderate (M) | Absolutely Extreme (AE) |
| 243 | Extreme (E) | Extreme (E) | Extreme (E) | Extreme (E) | Extreme (E) | Absolutely Extreme (AE) |

# Dissemination

## **Internationally indexed journals** (*Web of Science, SCI, Scopus*)[1]

1. **Sen, D. K.**, Datta, S., Patel, S. K. and Mahapatra, S. S. (2015). Multi-criteria decision making towards selection of industrial robot: exploration of PROMETHEE II method. *Benchmarking: An International Journal*, *22*(3), 465-487

2. **Sen, D. K.**, Datta, S. and Mahapatra, S. S. (2017). Extension of TODIM for Decision Making in Fuzzy Environment: A Case Empirical Research on Selection of Industrial Robot. *International Journal of Services and Operations Management*, *26*(2), 238-276.

3. **Sen, D. K.**, Datta, S. and Mahapatra, S. S. (2016). Extension of PROMETHEE for robot selection decision making: Simultaneous exploration of objective data and subjective (fuzzy) data. *Benchmarking: An International Journal*, *23*(4), 983-1014.

4. **Sen, D. K.**, Datta, S. and Mahapatra, S. S. (2016). Application of TODIM (Tomada de Decisión Inerativa Multicritero) for industrial robot selection. *Benchmarking: An International Journal*, *23*(7), 1818-1833.

5. **Sen, D. K.**, Datta, S. and Mahapatra, S. S. (2016). A TODIM-Based Decision Support Framework for G-Resilient Supplier Selection in Fuzzy Environment. *Asia-Pacific Journal of Operational Research*, *33*(5), 1650033-1 – 1650033-40.

6. **Sen, D. K.**, Datta, S. and Mahapatra, S. S. (2016). Decision Support Framework for Selection of 3PL Service Providers: Dominance-Based Approach in Combination with Grey Set Theory. *International Journal of Information Technology and Decision Making*, *15*, 1650047-1 to 1650047-33. Published Online. http://dx.doi.org/10.1142/S0219622016500474.

7. **Sen, D. K.**, Datta, S. and Mahapatra, S. S., Dominance Based Fuzzy Decision Support Framework for G-Resilient (Ecosilient) Supplier Selection: An Empirical Modeling, for *International Journal of Sustainable Engineering, 1-20* (Published online) http://dx.doi.org/10.1080/19397038.2017.1286410

8. **Sen, D. K.**, Datta, S., Patel, S. K. and Mahapatra, S. S. Green Supplier Selection in Fuzzy Context: A Decision Making Scenario on Application of Fuzzy-MULTIMOORA. *International Journal of Services and Operations Management. (In Press)*

## Other journals [1]

1. **Sen, D. K.**, Datta, S. and Mahapatra, S. S. (2015). Extension of TODIM Combined with Grey Numbers: An Integrated Decision Making Module. *Grey Systems Theory and Applications*, *5*(3): 367-391.

## Conferences [1]

1. **Sen, D. K.**, Datta, S., Patel, S. K. and Mahapatra, S. S. (2016). G-Resilient Supplier Selection in Fuzzy Environment: Application Potential of Satisfaction Function and Distance Based Approach. *4th Asia Conference on Mechanical and Materials Engineering,* July 14-16, 2016, Kuala Lumpur, Malaysia.

2. **Sen, D. K.**, Datta, S., Patel, S. K. and Mahapatra, S. S. (2016). A Conceptual Framework for Performance Evaluation of Industrial Supply Chain: Consideration of Traditional and Green Criteria. *1st International Conference on Emerging Trends in Mechanical Engineering,* September 23-24, 2016, Faculty of Science and Technology, The ICFAI Foundation of Higher Education (IFHE), Hyderabad, India.

3. **Sahu, S. K.**, Sen, D. K., Datta, S. and Mahapatra, S. S. (2016). Fuzzy Based Decision Support System for Supply Chain Performance Assessment: An Empirical Research using Fuzzy Numbers Set Theory. *1st International Conference on Emerging Trends in Mechanical Engineering,* September 23-24, 2016, Faculty of Science and Technology, The ICFAI Foundation of Higher Education (IFHE), Hyderabad, India.

4. **Sen, D. K.**, Datta, S., Patel, S. K. and Mahapatra, S. S. (2016). Fuzzy-TODIM for Industrial Robot Selection. *1st International Conference on Emerging Trends in Mechanical Engineering,* September 23-24, 2016, Faculty of Science and Technology, The ICFAI Foundation of Higher Education (IFHE), Hyderabad, India.

5. **Sen, D. K.**, Datta, S., Patel, S. K. and Mahapatra, S. S. (2016). On Understanding of Supply Chain Risks: Application of Fuzzy Set Theory (FST) and Interpretive Structural Modeling (ISM). *International Conference on Evolutions in Manufacturing: Technologies and Business Strategies for Global Competitiveness*, November 12-13, 2016, Organized by Department of Production Engineering, Birla Institute of Technology Mesra, Ranchi and The Institution of Engineers (India), Jharkhand State Centre (Under the Aegis of Production Engineering Division Board, IEI).

6. **Sen, D. K.**, Datta, S., Patel, S. K. and Mahapatra, S. S. (2016). Understanding of E-commerce Risks in Fuzzy Environment: A Decision Support Framework. *4th International Conference on Production and Industrial Engineering,* December 19-21, 2016 at Dr. B.R. Ambedkar National Institute of Technology, Jalandhar (India).

## Article under review [2]

1. **Sen, D. K.**, Datta, S. and Mahapatra, S. S., On Evaluation of Supply Chain's Ecosilient (G-Resilient) Performance Index: A Fuzzy Embedded Decision Support Framework, for **Benchmarking: an International Journal**, Emerald Group Publishing House, UK. **(Communicated)**

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[1]Articles already published, in press, or formally accepted for publication.
[2]Articles under review, communicated, or to be communicated.

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## I. Educational Details

| Course/Exam | Stream | Year | School/College | University | CGPA/% |
|---|---|---|---|---|---|
| **Ph.D.** | Regular | 2017 | ME (Spl: Production Engg.) | NIT, Rourkela | Thesis being submitted |
| M.Tech | ME (Spl. Industrial Engg.) | 2013 | TITECH Jabalpur, MP | RGPV Bhopal | 8.64 |
| B.Tech | ME | 2008 | REC Rewa, MP | RGPV Bhopal | 73.38 |
| Higher Secondary | Science+Maths | 2003 | CMA School Satna, MP | Board of Sec. Edu. Bhopal MP | 60 |
| High School | General | 2001 | CMA School Satna, MP | Board of Sec. Edu. Bhopal MP | 76.6 |

Dissertation Title (Ph.D.): ***Analysis of Decision Support Systems of Industrial Relevance: Application Potential of Fuzzy and Grey Set Theories***

## II. Personal Information

| | |
|---|---|
| Date of Birth | 11 May 1986 |
| Place of Birth | Satna (MP) |
| Marital Status | Married |
| Father's Name | Babulal Sen |
| Mother's Name | Bandana Sen |
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I hereby confirm that the information furnished above are true to the best of my knowledge and belief.

Dilip Kumar Sen